

IFT - UNESP
INSTITUTO DE FÍSICA TEÓRICA

PhD Thesis

IFT-T.004/2025

Dark Matter Search with Long-Lived Particles with the CMS Experiment at the LHC

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June 2025

O79d	Orzari, Breno Dark matter search with long-lived particles with the CMS experiment at the LHC / Breno Orzari. – São Paulo, 2025 233 f.: il. color. Tese (doutorado) – Universidade Estadual Paulista (Unesp), Instituto de Física Teórica (IFT), São Paulo Orientador: Thiago Rafael Fernandez Perez Tomei 1. Matéria escura - Astronomia. 2. Partículas (Física nuclear). 3. Aceleradores de partículas. I. Título
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DARK MATTER SEARCH WITH LONG-LIVED PARTICLES WITH THE CMS EXPERIMENT AT THE LHC

Tese de Doutorado apresentada ao Instituto de Física Teórica do Câmpus de São Paulo, da Universidade Estadual Paulista “Júlio de Mesquita Filho”, como parte dos requisitos para obtenção do título de Doutor em Física, Especialidade Física Teórica.

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São Paulo, 25 de junho de 2025.

Dedico esta tese aos meus pais Marcia Candido e Wagner Gilberto Orzari

Agradecimentos

Acima de tudo agradeço aos meus pais Marcia e Wagner, ao meu irmão Erick e ao meu sobrinho Pedro por todo apoio e confiança em minhas decisões, e por sempre me darem suporte e estarem ao meu lado nos momentos mais difíceis.

Agradeço à minha colega de profissão, namorada e melhor amiga Isabela pelas discussões sempre relevantes e pelo auxílio para superar mais essa etapa em minha vida. Também agradeço aos meus colegas Danyellen, Dener e Gabriel pelos momentos de descontração e debates que sempre existirão apesar da distância.

I would like to thank my dear friends Adriano, Chara and Dimitris for all the time we spent together, whether in person or virtually.

Agradeço ao meu orientador Thiago Tomei por toda a ajuda profissional e pessoal que me proporcionou durante esses anos, e por ser quem me fez chegar onde estou.

Agradeço aos meus colegas de turma do IFT por todo o suporte e pelos bons momentos. Também gostaria de agradecer aos professores e ao pessoal técnico-administrativo do IFT por todo apoio.

Agradeço à todos do SPRACE e do NCC por todo o apoio. Em particular, gostaria de agradecer aos professores César, Eduardo, Pedro, Sandra e Sérgio cujos conselhos me guiaram na confecção deste trabalho. Agradeço também aos meus colegas do SPRACE: Bruno, Cauê, Julia, Márcio, Matheus, Valerie e Zain por todos os bons momentos.

O presente trabalho foi realizado com o apoio da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Código de financiamento 001.

Agradeço à Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) pelo financiamento do projeto de pesquisa (processo nº 2020/06600-3, Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP)), possibilitando a produção desta tese, e pela possibilidade de executar um projeto de pesquisa no CERN, no formato de BEPE, processo nº 2022/07942-0. As opiniões, hipóteses e conclusões ou recomendações expressas neste material são de responsabilidade do autor e não necessariamente refletem a visão da FAPESP.

*“Do not pity the dead,
Harry, pity the living,
and above all those
who live without love,”*

Albus Dumbledore, Harry Potter and the Deathly Hallows.

Resumo

Neste trabalho, dois projetos são apresentados: melhorias no algoritmo de reconstrução de traços utilizando o detector de pixels do CMS e uma busca por partículas de matéria escura no detector do CMS. As melhorias no algoritmo de reconstrução de traços de pixels do HLT foram realizadas para abordar dois problemas: a difícil manutenibilidade, dado que o código da reconstrução é duplicado, e a exclusividade para um determinado dispositivo acelerador no processamento da reconstrução de eventos. O uso de uma biblioteca de portabilidade de performance permite a solução desses problemas, tendo apenas uma cópia do código compilada para dispositivos distintos. Além de resolver ambos os problemas, essas melhorias desempenharão um papel fundamental durante a era HL-LHC. A busca por partículas de matéria escura é realizada em termos do modelo AMSB, que contém uma partícula instável carregada, o chargino, que decai no interior do detector do CMS em produtos que não são reconstruídos. A assinatura desse processo no detector é a de um traço de partícula carregada que desaparece nas camadas mais internas. Um dos produtos do decaimento é o neutralino, que é a partícula supersimétrica mais leve e é um candidato à matéria escura. A busca por traços evanescentes foi feita utilizando $62,5 \text{ fb}^{-1}$ de dados coletados pelo experimento do CMS com uma energia de centro de massa de $\sqrt{s} = 13.6 \text{ TeV}$ durante 2022 e 2023. Dado que esta análise de dados ainda está cega pela colaboração do CMS, os resultados são interpretados em termos de regiões de exclusão esperadas com CLs de 95% usando dados das regiões de controle da busca. Considerando apenas os dados do *Run 3*, espera-se a exclusão de um chargino do tipo wino até uma massa de 777 (405) GeV, para um tempo de vida de 3 (0.2) ns, e de um chargino do tipo higgsino até uma massa de 650 (354) GeV, para um tempo de vida de 3 (0.2) ns. Ao combinar este resultado com os resultados do *Run 2* anterior, espera-se a exclusão de um chargino do tipo wino até uma massa de 904 (511) GeV, para um tempo de vida de 3 (0.2) ns, e de um chargino do tipo higgsino até uma massa de 762 (437) GeV, para um tempo de vida de 3 (0.2) ns.

Palavras Chaves: Matéria Escura; Física de Partículas; Aceleradores de Partículas; Detectores de Partículas; Física além do Modelo Padrão.

Áreas do conhecimento: Física; Física de Partículas; Física de Altas Energias.

Abstract

In this work, two projects are presented: improvements to the CMS pixel tracking algorithm and a search for dark matter particles at the CMS detector. The improvements to the HLT pixel tracks reconstruction algorithm were performed to address two issues: the hard maintainability, given that the reconstruction code is duplicated, and the exclusivity to a given accelerator device in the process of reconstructing events. The usage of a performance portability library allows for the solution of these issues, by having only one piece of the code that is compiled for distinct devices. Besides solving both issues, these improvements will play a fundamental role during the HL-LHC era. The search for dark matter particles is performed in terms of the AMSB model, which contains a charged unstable particle, the chargino, that decays inside the CMS detector into products that are not reconstructed. This process signature in the detector is that of a charged particle track that vanishes in the internal layers. One of the decay products is the neutralino, which is the lightest supersymmetric particle and is a dark matter candidate. The search for disappearing tracks was done using 62.5 fb^{-1} data collected by the CMS experiment with a center-of-mass energy of $\sqrt{s} = 13.6 \text{ TeV}$ during 2022 and 2023. Given that the CMS collaboration still blinds this data analysis, the results are interpreted in terms of expected exclusion regions with 95% CLs using data from the control regions of the search. Considering the Run 3 data only, a wino-like chargino is expected to be excluded up to a mass of 777 (405) GeV for a lifetime of 3 (0.2) ns, while a higgsino-like chargino is expected to be excluded up to a mass of 650 (354) GeV for a lifetime of 3 (0.2) ns. When combining this result to the previous Run 2 results, a wino-like chargino is expected to be excluded up to a mass of 904 (511) GeV for a lifetime of 3 (0.2) ns, while a higgsino-like chargino is expected to be excluded up to a mass of 762 (437) GeV for a lifetime of 3 (0.2) ns.

Keywords: Dark Matter; Particle Physics; Particle Accelerators; Particle Detector; Beyond the Standard Model Physics.

Knowledge Areas: Physics; Particle Physics; High Energy Physics.

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List of Acronyms

2HDM Two-Higgs doublet model	CSC Cathode strip chamber
ΛCDM Lambda cold dark matter	CTF Combinatorial track finder
ALICE A Large Ion Collider Experiment	DA Deterministic annealing
ALP Axion-like particle	DDet Direct detection
Alpaka Abstraction library for parallel kernel acceleration	DFS Depth-first search
AMSB Anomaly-mediated SUSY breaking	DJR Differential jet rate
aNNLO Approximate next-to-next-to leading order	DM Dark matter
AOD Analysis data object	DNN Deep neural network
ATLAS A Toroidal LHC Aparatus	DS Dark sector
BDT Boosted decision tree	DT Drift tube
BG Background	EB ECAL barrel
BSM Beyond the Standard Model	ECAL Electromagnetic calorimeter
CERN European Organization for Nuclear Research	EE ECAL endcap
CKF Combinatorial Kalman filter	FPGA Field programmable gate arrays
CL Confidence level	GEM Gas electron multiplier
CMB Cosmic microwave background	GPU Graphics processing unit
CMS Compact Muon Solenoid	GR General relativity
CMSSW CMS reconstruction and analysis software	GT Global trigger
CPU Central processing unit	HB HCAL barrel
	HCAL Hadronic calorimeter
	HE HCAL endcap
	HEP High-energy physics
	HF HCAL forward
	HL-LHC High-luminosity LHC

HLT	High-level trigger	PDF	Parton distribution function
HO	HCAL outer	PF	Particle flow
ID	Identification	PS	Parton shower
IDet	Indirect detection	PU	Pileup
IDM	Inelastic dark matter	PUPPI	Pileup-per-particle identification
IP	Interaction point	PY8	Pythia
ISR	Initial state radiation	QCD	Quantum chromodynamics
JEC	Jet energy correction	RMS	Root mean square
JER	Jet energy resolution	RPC	Resistive plate chamber
L1T	Level 1 trigger	RPV	R-parity violating
LHC	Large Hadron Collider	SC	Supercluster
LHCb	Large Hadron Collider beauty	SF	Scale factor
LLP	Long-lived particles	SI	Spin-independent
LO	Leading order	SIMD	Single instruction, multiple data
LSP	Lightest supersymmetric particle	SM	Standard Model
MACHO	Massive compact halo object	SoA	Structure of array
mAMSB	Minimal AMSB	SS	Same-sign
MC	Monte Carlo	SUSY	Supersymmetry
ME	Matrix element	T&P	Tag-and-probe
MG5	MadGraph5	TBB	Thread building block
MIP	Minimum ionizing particle	TIB	Tracker inner barrel
ML	Machine learning	TID	Tracker inner disk
MOND	Modified newtonian dynamics	TEC	Tracker endcap
MSSM	Minimal supersymmetric SM	TOB	Tracker outer barrel
NFW	Navarro-Frenk-White	TP	Trigger primitive
NNLL	Next-to-next-to leading logarithmic	VEV	Vacuum expectation value
PBH	Primordial black hole		

Glossary

Alpaka C++ template library designed for performance portability across distinct hardware architectures. It allows for code to be written once and be compiled for distinct hardware such as CPUs and GPUs.

AMSB SUSY model where the mass difference between its lightest chargino and neutralino is on the order of m_π .

Dark matter Hypothetical type of matter that does not interact electromagnetically. It can be inferred from astronomical and cosmological gravitational measurements.

Disappearing track BSM charged particle that decays in the inner layers of a modern particle detector tracker.

E_{calo} Energy measured by the calorimeters that is associated with a charged particle track.

Hit Signal from a charged particle measured in a tracker layer.

LLP Particles that live long enough to leave a detectable signal in a modern particle detector.

Missing hit Status of active tracker layers that should contain a hit, estimated from the charged particle trajectory, but does not have a compatible measurement. It is divided into inner (before the first valid hit), middle (in between the first and the last valid hits), and outer (after the last valid hit) missing hit.

Standard Model Theoretical model that describes all known elementary particles and their interactions, except for gravity.

Tracker Detector that measures the trajectory of charged particles.

Chapter 1

Introduction

The Standard Model of particles and fields (SM) is one of the most extensively tested theories of physics. With the Higgs boson discovery, the advancements in the experimental techniques needed to assess the validity of the SM were shown to match its predictive power, given that its measured properties match very closely the theory expectations. However, there are some phenomena that it cannot explain.

Astrophysical and cosmological observations have shown that some gravitational anomalies exist on different scales of size, the source of which is yet to be explained. These anomalies usually indicate that the gravitational effects that should be seen when considering Newton's universal law of gravitation or general relativity have to be exaggerated to match the observations. Several distinct proposals exist to explain these anomalies. One possible explanation is that the universe is made of more matter than what is visible in the electromagnetic spectrum. This extra matter, which received the name of dark matter (DM), was proposed to exist almost a century ago. None of the SM particles adjust to the observed properties of this matter, implying that many new extensions to the SM are being proposed with new particles to explain this phenomenon.

Within the distinct beyond the standard model (BSM) models, the interaction between SM and DM particles can occur to produce a visible signal that can be seen by modern experiments. In the high-energy physics (HEP) context, the production of DM particles is possible from the collision of SM particles in particle accelerators such as the Large Hadron Collider (LHC), where the detection of the resulting products is performed by particle detectors such as the Compact Muon Solenoid (CMS). One of the main goals of particle detectors is to be able to measure the properties of the particles as accurately and quickly as possible in a process that is called event reconstruction. Nowadays, the state of the art in terms of event processing is the usage of heterogeneous computing systems to accelerate

the reconstruction of physics objects without loss of efficiency. This implies the need to upgrade the existing algorithms to be processed with distinct accelerator devices.

The analysis of the collected data can then be used for searches for BSM models, which could explain the missing matter phenomena. One of such searches is for disappearing tracks, where a BSM charged particle decays inside the inner layers of a particle detector, with decay products being undetected, giving the impression that the particle "vanished". One of the decay products, is a dark matter candidate.

The structure of this work is as follows: Chapter 2 describes some of the evidences for the existence of DM, relevant models used for searching for DM particles and possible detection methods; Chapter 3 gives a description of the LHC and the CMS detector, focusing on the characteristics of the CMS subdetectors, and the triggering system; Chapter 4 describes the experimental signature expected in the disappearing tracks search, some of the previous searches for this type of signature, and the current strategy for the search of disappearing tracks; Chapter 5 details the reconstruction of charged particles trajectories performed by the CMS detector, and describes an upgrade to the pixel tracks reconstruction algorithm; Chapter 6 details the analysis performed in the search for disappearing tracks, and presents preliminary results obtained from data collected by the CMS experiment during 2022 and 2023. Finally, Chapter 7 discusses the obtained results and show the conclusions of the work performed. To ease the understanding of the varied subjects in this work, Figure 1.1 shows how the chapters are linked.

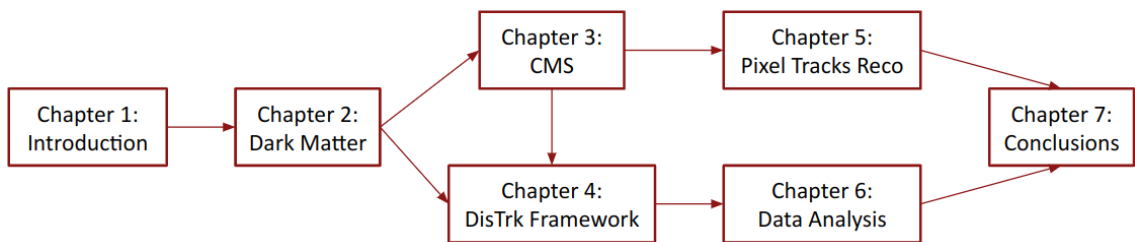


Figure 1.1: Scheme of how the subjects in each chapter of this work are linked.

Chapter 2

Evidences, Models, and Searches for Dark Matter

Despite being one of the most successful theories in modern physics, the Standard Model (SM) [1–5] has its limitations. It describes the behavior of all known subatomic particles and almost every interaction between them, but there are still mysteries it doesn't explain. One of the biggest gaps is dark matter, or "missing" matter, which makes up a large part of the universe.

2.1 Dark Matter Evidences

With cosmological and astronomical probes, it is possible to know how much dark matter (DM) exists in the universe, both on the scale of the observable universe and in smaller regions, such as galaxies. It is also possible to observe that dark matter does not seem to interact much, if at all, with particles from the Standard Model (aside from gravity), and it appears to be stable over billions of years. This chapter goes over the evidence for dark matter, taking a historical approach based on Ref. [6], describes some of the most commonly studied theoretical models of a hypothesized dark matter particle, and dives into how scientists are trying to detect it while going through the reasons to why no particle from the Standard Model fits as a dark matter candidate.

The earliest evidence (as described in Ref. [7]) emerged in 1930, when astronomer Fritz Zwicky, applying the virial theorem to the motion of galaxies (then known as nebulae) within galaxy clusters, observed that the luminous matter in these clusters accounted for only a portion of the total cluster mass. The virial theorem is derived by analyzing the equations of motion for a galaxy i with mass M_i at a distance r_i :

$$\vec{r}_i \cdot \left(M_i \frac{d^2 \vec{r}_i}{dt^2} = \vec{F}_i \right) \rightarrow \frac{1}{2} \frac{d^2 (M_i r_i^2)}{dt^2} - M_i \left(\frac{dr_i}{dt} \right)^2 = \vec{r}_i \cdot \vec{F}_i. \quad (2.1)$$

Summing over all the galaxies in the cluster, and defining $\Theta \equiv \sum_i M_i r_i^2$ (polar moment of inertia), $Vir \equiv \sum_i \vec{r}_i \cdot \vec{F}_i$ ("virial" of the cluster) and $K_T = \frac{1}{2} \sum_i M_i \left(\frac{dr_i}{dt} \right)^2$ (total kinetic energy),

$$\frac{1}{2} \frac{d^2 \Theta}{dt^2} = Vir + 2K_T. \quad (2.2)$$

In a static cluster, the average of the time derivative of Θ is zero, and the so-called virial theorem remains

$$\overline{Vir} = -2\overline{K_T}. \quad (2.3)$$

Assuming

$$Vir = U = - \sum_{i < j} G_N \frac{M_i M_j}{r_{ij}} \rightarrow \text{Law of Universal Gravitation}, \quad (2.4)$$

with $r_{ij} \equiv |\vec{r}_j - \vec{r}_i|$, and that M_T , the mass of the cluster, is spherically distributed with radius R_T ($\rho = M_T / V_T = \frac{3M_T}{4\pi R_T^3}$), the virial will be

$$\begin{aligned} U = \int V(r) dm &= - \int_0^{R_T} \frac{G_N}{r} \frac{4\pi r^3 \rho}{3} 4\pi r^2 \rho dr = \frac{-16\pi^2 G_N \rho^2 R_T^5}{15} = \\ &= \frac{-16\pi^2 G_N R_T^5}{15} \left(\frac{3M_T}{4\pi R_T^3} \right)^2 = -\frac{3G_N M_T^2}{5R_T}. \end{aligned} \quad (2.5)$$

Using that $2\overline{K_T} = \sum_i \overline{M_i v_i^2} = \sum_i M_i \overline{v_i^2}$, when averaging the galaxies' velocity, finally, one can determine

$$\sum_i M_i \overline{v_i^2} = M_T \overline{v^2} \rightarrow M_T = \frac{5R_T \overline{v^2}}{3G_N}. \quad (2.6)$$

As an example, using the Coma cluster in which the average speed of galaxies measured is $\overline{v_s^2} = \overline{v^2}/3 \approx 10^{12} \text{ m}^2/\text{s}^2$ with total radius $R_T \approx 10.000.000$ light years,

the value of M_T is approximately

$$M_T \approx \frac{5 \times 9,46 \times 10^{22} \times 10^{12} \frac{\text{m}^3}{\text{s}^2}}{6,67 \times 10^{-11} \frac{\text{m}^3}{\text{kg} \cdot \text{s}^2}} \approx 7 \times 10^{45} \text{ kg} \approx 3.5 \times 10^{15} M_{\odot}, \quad (2.7)$$

where $M_{\odot}$ is a solar mass.

It is known that, on average, each galaxy contains about 10^{11} stars, and since the Coma cluster has roughly 1000 galaxies, the ratio of the cluster's mass to its luminosity (with luminosity being defined by the light intensity coming from the cluster measured via photometry [8] in the infrared, visible and/or ultraviolet wavelengths, displayed in terms of the sun's luminosity $L_{\odot}$, which is proportional to the number of stars in the cluster) is approximately $35 M_{\odot}/L_{\odot}$. If there were no dark matter in the universe, this ratio would be expected to be $1 M_{\odot}/L_{\odot}$. With more accurate measurements of these quantities, current estimates suggest that this ratio can reach up to $400 M_{\odot}/L_{\odot}$, depending on the cluster in question.

The second evidence (following the approach in Ref. [7]) was uncovered through the extensive research conducted by Vera Rubin and her collaborators in the late 1970s [9], particularly in their measurement of the rotation velocities of about 20 galaxies (in one of her most significant studies). The issue arises from the unusual shape of these curves, indicating that there must be more mass beyond the galaxies than what is accounted for by luminous matter.

In a circular orbit, the velocity of a particle in an axisymmetric galaxy varies with the distance to the galaxy center as:

$$v_c^2(r) = \frac{G_N M(r)}{r}, \quad (2.8)$$

where r is the radial coordinate and $M(r)$ is the mass distribution as function of the distance to the galaxy center. For a mass M concentrated in a point, the velocity will be

$$v_c(r) = \sqrt{\frac{G_N M}{r}}. \quad (2.9)$$

In the simplest case, i.e., with a constant density ρ , the velocity v_c of a particle

orbiting a spherically symmetric galaxy with radius R is given by

$$v_c(r) = \begin{cases} \sqrt{\frac{4\pi G_N \rho}{3}} r & , r \leq R, \\ \sqrt{\frac{4\pi G_N R^3 \rho}{3r}} \propto r^{-1/2} & , r > R. \end{cases} \quad (2.10)$$

However, the mass distribution of an axisymmetric spiral galaxy like the Milky Way differs significantly from that of a spherical galaxy. The calculation outlined above is beyond the scope of this thesis. Nevertheless, the outcome should show that v_c increases almost linearly at small r , and behaves as $r^{-1/2}$ at large r [10].

With the development of radio telescopes, Rubin was able to measure and catalog the rotation velocities of axisymmetric spiral galaxies. This was made possible by the Doppler shift of the 21 cm hydrogen atom line, which enabled the measurement of velocities at distances up to 120 kpc (depending on the galaxy's size) from the galactic center, where 1 parsec equals approximately 3.26 light years. The results were surprising: in smaller galaxies ($0 \text{ kpc} \leq R \leq 35 \text{ kpc}$), v_c increased rapidly at small r ($r \approx 5 \text{ kpc}$) and continued to grow for larger r ; in larger galaxies ($R \geq 50 \text{ kpc}$), v_c also increased quickly at smaller r ($r \approx 5 \text{ kpc}$), but then stayed constant; both findings contradict the $r^{-1/2}$ behavior, as shown in Figure 2.1 below.

Some earlier results, before Rubin's work, already suggested a difference in the form of v_c . Around 1970, astronomer Ken Freeman proposed an explanation for this discrepancy [11], suggesting the existence of a spherical dark matter "halo" around galaxies, with $M_{DM}(r) \propto r$ for large r .

Different models have been used to try to describe the mass density profile of such halos in simulations, such that they could fit the observed data. The most commonly referred to are the Navarro-Frenk-White (NFW) [13, 14], the Moore profile [15], and the Jaffe profile [16], among others. These models describe the halos using two parameters: the halo scaling density ρ_0 and radius R_s . In general, the density profile has the following format ¹:

$$\rho(r) = \frac{\rho_0}{\left(\frac{r}{R_s} \left(1 + \frac{r}{R_s} \right) \right)^2}, \quad (2.11)$$

¹Using the NFW profile as an example, since it is still one of the most commonly used profiles; usually the power of the r and R_s related terms are different in other profiles.

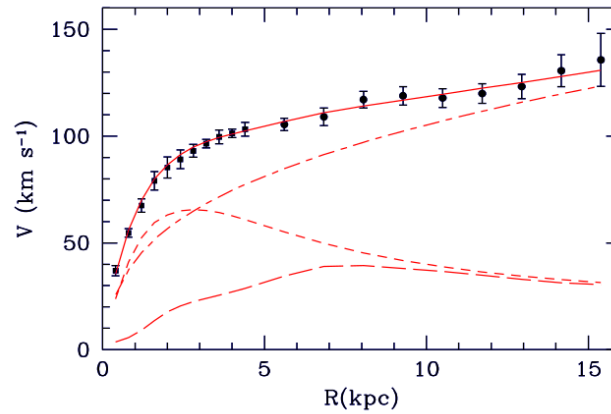


Figure 2.1: Measured rotation velocity of galaxy M33 as a function of the distance from its center (black circles). The red curves represent the fit to the data points (solid line), the contribution from dark matter (dashed-dotted line), the contribution from stars (short dashed line), and the contribution from intra-galactic gas (long dashed line). Source: [12].

which causes the cusp-core problem, i.e., the density diverges as r goes to 0 (near the core of the galaxy). Other commonly used profiles avoid this issue by modifying the denominator of Equation 2.11 [17] or by using a profile defined by an exponential relation [18]. Besides all of these efforts to try to fit the data, most of these profiles were not based on a physical theory, and, only more recently, different approaches have tried to derive an expression for the mass density profile based on the formation history of the DM halos, the probability distribution of particles in them, and many others [19–22].

The third piece of evidence is highly significant and has provided important constraints on the properties of dark matter. It relates to the collisions of galaxy clusters, which, following the discovery and enhanced observations of the gravitational lensing phenomenon, have been observed from a different perspective [23].

Gravitational lensing occurs when light from a distant source is deflected by a very massive object, causing the image seen by an observer to be distorted. This effect is explained by the space-time distortion caused by massive objects that are expected from the general relativity theory (GR) [24]. There are two types of final images: one where the effect of gravitational lensing is weak, meaning the deflection is too small to cause noticeable distortion, and the light experiences

only a minor increase in intensity; and another where the effect is strong, resulting in a distorted image, or even multiple images of the same object.

One of the most well-known examples that demonstrate the utility of gravitational lensing in the study of dark matter is the bullet cluster (see Figure 2.2). The bullet cluster (1E 0657-56) consists of the collision of two galaxy clusters, where the smaller of them can be observed to have the shape of a bullet. Although very dim, it can be observed in the Carina constellation, about 6° east-southeast of the star Canopus. When considering the matter content of galaxy clusters, in addition to the galaxies' visible light sources, the majority of the visible mass in galaxy clusters is of intra-cluster gas. In galaxy cluster collisions (such as in the bullet cluster), this gas is heated and emits X-rays, allowing for precise estimation of its location, quantity, and mass. However, in the case of the bullet cluster, measurements from gravitational lensing suggest that, first, not all of the cluster's mass is visible, and second, most of the mass is not located with the intra-cluster gas, but rather farther from the center of the collision.

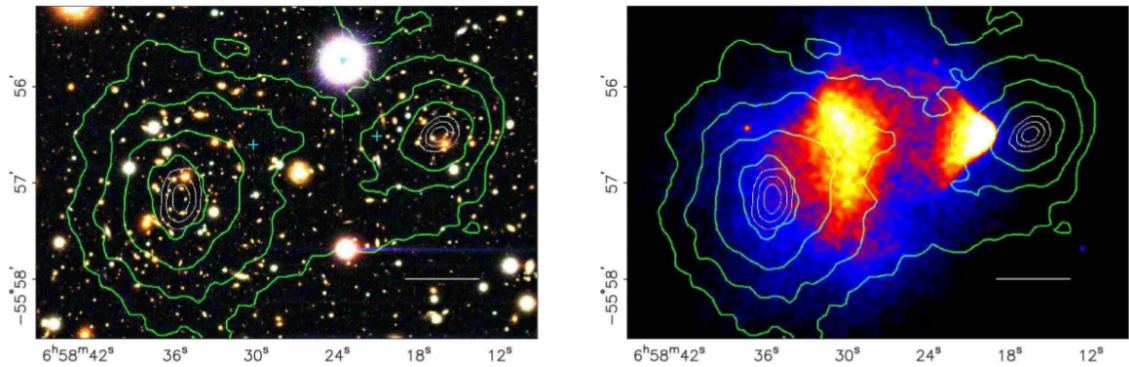


Figure 2.2: Left: overlay of visible spectrum image with gravitational lensing contour lines (in green) of the bullet cluster. Right: overlay X-ray image (with a blue to white color scale) with gravitational lensing contour lines (in green). Source: [23].

This image suggests the presence of at least one significant constraint on the properties of a dark matter particle. It shows that the galaxies (which do not collide) follow the highest concentration of mass (indicated by the green contour lines), while the gas (depicted by the blue to white color scale), which does collide, becomes concentrated in the center of the collision. From the region with the highest mass concentration, as determined by gravitational lensing, and by using

detailed hydrodynamic simulations [25], it is possible to estimate the density of the dark matter in the cluster and establish an upper limit for the self-interaction cross section of this type of matter, which is estimated to be $\sigma_{\chi\chi}/m_\chi \lesssim 1 \text{ cm}^2/\text{g}$ (or $\sigma_{\chi\chi}/m_\chi \lesssim 1.8 \text{ barn}/\text{GeV}^2$ in units commonly used in high energy physics (HEP)).

One of the most recent evidence comes from measurements of the Cosmic Microwave Background (CMB) [26–28]. The Concordance Cosmological Model [29] suggests that shortly after the Big Bang, there was a quark and gluon soup, known as the Quark-Gluon Plasma, along with charged and neutral leptons, photons, and massive bosons. As the universe cooled, it became possible to form new structures such as mesons, baryons, atomic nuclei, and more.

Before 380,000 years of expansion, the universe was made up of positive ions, electrons, photons, and neutrinos. During this period, the conditions were favorable for interactions between photons and charged particles, meaning that no photons could escape. Afterward, in the phase known as the "recombination epoch", the temperature of the universe dropped below the energy required to ionize hydrogen, allowing neutral atoms to form and become "transparent" to the existing radiation, which then began traveling through space.

These initial photons make up the CMB and carry crucial information about the expansion and composition of the universe. Upon measuring this background radiation, an important feature was observed: its temperature (around 2.725 K on average) is *almost* isotropic across space. There are tiny fluctuations, about 1 part in 10,000, in the temperature. Figure 2.3 shows an image from the Planck experiment [27] depicting the temperature variations in the CMB.

The angular power spectrum, which is defined in terms of the coefficients of the expansion in spherical harmonics of this temperature variation, can be obtained as:

$$\Delta T(\hat{n}) = \sum_{\ell=0}^{\ell_{\max}} \sum_{m=-\ell}^{\ell} a_{\ell m}^{TT} Y_{\ell m}(\hat{n}), \quad (2.12)$$

$$C_\ell^{TT} = \frac{1}{2\ell+1} \sum_{m=-\ell}^{\ell} |a_{\ell m}^{TT}|^2. \quad (2.13)$$

²Here using natural units in which $c = 1$

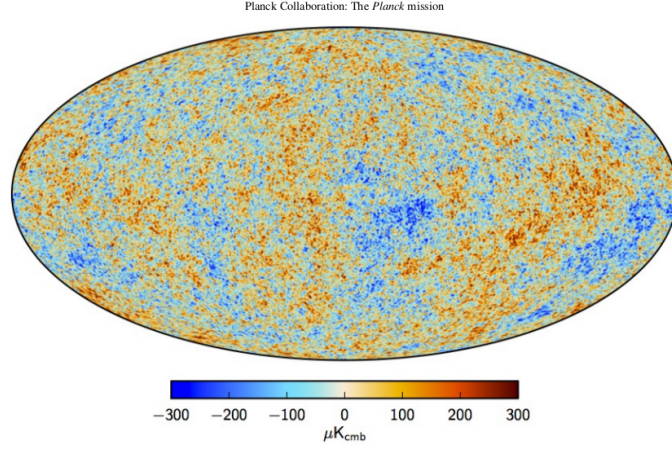


Figure 2.3: Planck collaboration measurements of the temperature variations of the CMB. The scale is in μK . Source: [27].

The data obtained by the Planck collaboration and the fit to the data are shown in Figure 2.4. By convention, the unit is

$$\mathcal{D}_\ell^{TT} = \frac{C_\ell^{TT} \ell(\ell+1)}{2\pi}. \quad (2.14)$$

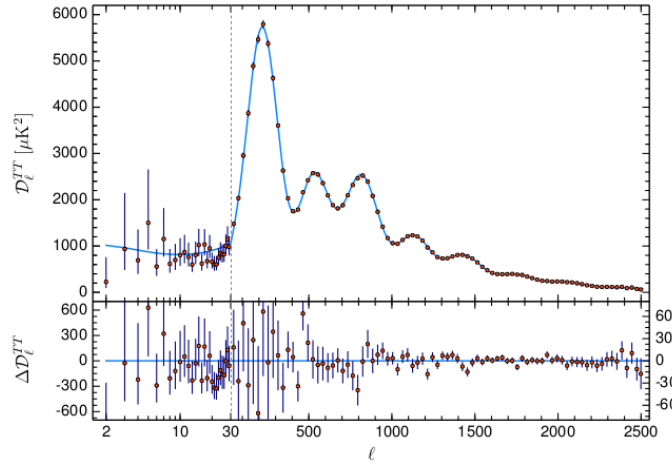


Figure 2.4: Data (orange circles) obtained by the Planck collaboration for $\mathcal{D}_\ell^{TT}$ versus ℓ . The fit to the data points using the ΛCDM model is given by the blue curve. Source: [28].

The theoretical prediction, shown by the blue curve, is provided by the lambda cold dark matter (ΛCDM) model that is, currently, the model that best accounts for all observed cosmological data, which proposes that the universe is composed

of ordinary matter (baryons, electrons, photons, and neutrinos), "cold" dark matter (currently non-relativistic, i.e., their average velocity v is much smaller than the speed of light in a vacuum $v/c \ll 1$, or, due to structure formation constraints, that their free streaming length, i.e., the distance the dark matter particle travels unobstructed, is on the order of 100 light-years), and a cosmological constant Λ . This model also assumes that general relativity accurately describes gravitational interactions. From Λ CDM [28], the current energy content of the observable universe can be divided into 68.9% of what is called dark energy, which is denoted by the cosmological constant, and 31.1% of matter that is further divided into 15.8% of visible matter and 84.2% of dark matter.

Using this fit, the model estimates the quantity of each of these components based on our knowledge of visible matter while respecting other constraints related to dark matter production in the early universe. This assumption is also crucial for forming gravity wells early in the universe that were deep enough to develop into the large-scale structures [30] we observe today.

Several hypotheses were suggested to explain all of this evidence. Some of the most cited hypotheses are the existence of dark (that doesn't emit light) objects, such as massive compact halo objects (MACHOs) [7, 31] made of ordinary matter or primordial black holes (PBHs) [32], distinct descriptions of the gravitational force, such as modified Newtonian dynamics (MOND) [33] models, and the assumption of it being made of a particle that isn't part of the Standard Model.

Objects that fit the category of MACHOs are planetary/stellar-sized objects such as gaseous planets, brown dwarfs, black holes, etc., that emit none or at least a very small amount of light, that are faint enough not to be directly observed with telescopes from Earth. Currently, those objects have already been ruled out as possible candidates of the complete 84.2% DM content of the universe, although an upper bound of 15% [34] of galaxy dark matter might be made of these compact objects that do not emit light. To search for such objects, the technique known as microlensing [35], which is based on very small brightness fluctuations observed when a "dark" massive object passes in front of a distant bright object, is used to infer the properties and density of MACHOs. This same technique is used to study the existence and estimate the density of PBHs. Even though PBHs of masses larger than $\sim 10^{-8} M_{\odot}$ have been ruled out by microlensing searches, the lower

bound on the mass of such objects is as low as $\sim 10^{-19} M_{\odot}$ [7], which are yet to be explored using a myriad of other techniques [32].

Models with MOND have been proposed as a possible explanation for the distinct behavior of objects on astronomical and cosmological scales for almost four decades [33]. In these models, the relationship of the force exerted by massive objects over large distances is distinct from the expected from Newtonian dynamics, since it proposes a larger acceleration for objects that are in regions with smaller gravitational fields. Even though several experiments show that MOND adjusts the observations better than GR [36], it only holds its accuracy for a given or a few pieces of evidence at each time, needing to be fine-tuned for the different phenomena that point toward the existence of dark matter.

One of the hypotheses that fit well within the DM evidence on all scales is that dark matter is composed of subatomic particles [7]. This proposition allows for distinct theoretical models to "adjust" the parameters of these particles to regulate the DM density and distribution in the universe. In summary, from all the evidence discussed above, it is possible to infer certain properties of this potential candidate:

- Stable on cosmological timescales: should have existed at least since the recombination epoch;
- Electrically neutral: does not interact with photons;
- "Cold" enough to account for the observed structures in the universe and the current dark matter density observed within the Λ CDM model;
- Interacts gravitationally with Standard Model particles and may also have a very weak coupling that is not yet identified.

One might consider whether any of the Standard Model particles could explain the missing matter phenomenon. However, the characteristics listed above rule out this possibility. First, a dark matter particle cannot interact electromagnetically, excluding all quarks, charged leptons, the $W^{\pm}$ bosons, and the photon. It also cannot interact via the strong force, which rules out gluons, and it must be stable on cosmological timescales, thus eliminating the Z and H bosons as candidates. Neutrinos were once considered as potential dark matter particles, but they are too fast, or "hot", and do not align with the Λ CDM model.

Given its characteristics, there are several ways to search for a potential dark matter candidate. The experimental setups rely on possible interactions of the DM particle with the SM in different ways, which are complementary to each other.

2.2 Types of Searches for Dark Matter Particles

Considering the case where the missing matter phenomena are caused by a non-relativistic dark matter particle, there are a few different ways to observe that particle, as shown in Figure 2.5:

- Direct Detection (DDet): the interaction between a DM and an SM particle could generate a visible signal;
- Indirect Detection (IDet): the detection of SM particles coming from DM particles decay or annihilation is also a potential visible signal;
- Production at colliders: given that the DM particle could interact with SM particles, it could be produced at particle accelerators.

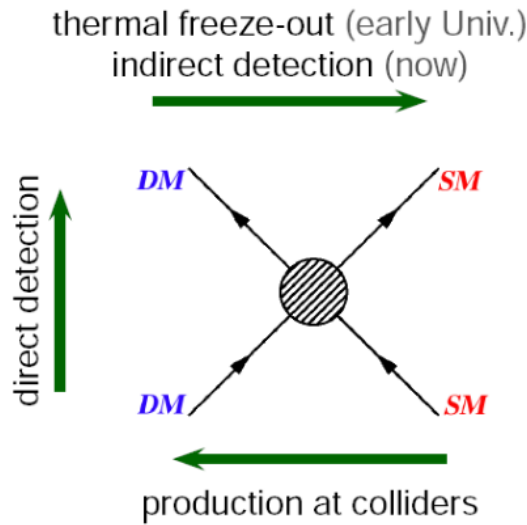


Figure 2.5: Diagram for dark matter detection. From left to right: dark matter annihilation (indirect detection); from bottom to top: dark matter interaction with Standard Model particles (direct detection); from right to left: dark matter production in particle colliders.

A direct detection signal [37, 38] can help determine the mass of the dark matter particle, as the type of signal observed in a given detector depends on it. Additionally, the spin of the particle can be inferred from the number of interactions with a

particular material in the detector, which is directly influenced by the interaction cross section and, consequently, the spins of the involved particles.

This signal may appear as photons emitted by an excited nucleus after being struck by a DM particle, scintillation light from the nucleus recoil, atomic ionization, or lattice vibrations in the form of phonons, corresponding to MeV to GeV mass DM particles. It may also appear as electron transitions in crystal band gaps, electron recoil from DM-nucleon scattering, or phonon excitation in crystals from a few keV to a few MeV DM particle masses. Experiments relying on these methods of DM detection are XENONnT, LZ, DarkSide-50, PandaX-4T, CRESST-III, and others [39–45].

An indirect detection signal [46, 47] will vary depending on the type of DM particle considered. Examples include an excess of gamma-ray photons, neutrinos, or cosmic rays, concerning the expected background from known sources. These can be detected using neutrino detectors and telescopes on Earth, or through particle detectors as telescopes located in Earth's orbit, such as Fermi-LAT, H.E.S.S., MAGIC, IceCube, and many more [48–54].

The final method, which is the focus of this work, involves the production of DM particles in hadron colliders³ and their "detection" in particle detectors [55]. The main challenge of this method is the production of the DM particles themselves, as a significant cross section is required for their creation in a particle collider. To compensate for the lack of a cross section large enough to easily observe these particles, particle accelerators have very large luminosity, or, in other words, a very large rate of particle collisions.

Furthermore, since DM particles interact only rarely with Standard Model particles, no signal of their interaction can be produced directly in a particle detector during a collision experiment. However, their production can be inferred through a detailed analysis of the collisions recorded in the detector. The expected signal left from the DM particles in particle detectors is directly dependent on the theoretical model suggesting a given type of beyond the Standard Model (BSM)

³The choice of hadron colliders is due to the straightforward capability of these collisions to explore a larger range of center-of-mass energy, E_{CM} , without changing the parameters of the colliding beams of particles. This makes hadron colliders the best choice for the discovery of new particles.

particles and their characteristics.

2.3 An Overview of Models for Dark Matter Particles

From the characteristics of possible DM particles discussed above, there are several distinct theoretical models for including new particles to extend the SM and accommodate the dark matter evidence. Following the outlook given in Ref. [56] to introduce models that are commonly studied in particle colliders, these models can be categorized as simplified models, which add a pair of particles to the Standard Model, and extended models.

2.3.1 Simplified Dark Matter Models

The simplest DM models propose the addition of a massive fermionic DM particle, denoted by χ , and a massive mediator that couples this particle to the SM. This coupling to the SM is needed, otherwise, it would not be possible to produce the dark matter fermion inside a particle collider. These cases are also referred to as portals, given that the mediator serves as a gateway that connects SM to DM. This mediator can be a scalar, pseudo-scalar, vector, or axial-vector [57], depending on the model. It can also interact differently with SM and DM particles, which implies distinct signals to be searched for in particle colliders.

Equations 2.15–2.18 show the interaction terms that are added to the Lagrangian of the SM in the scalar, pseudo-scalar, vector, and axial-vector models, respectively:

$$\mathcal{L} \supset y_{\text{DM}} S \bar{\chi} \chi + \frac{S}{\sqrt{2}} \sum_f y_f \bar{f} f, \quad (2.15)$$

$$\mathcal{L} \supset -iy_{\text{DM}} P \bar{\chi} \gamma^5 \chi - i \frac{P}{\sqrt{2}} \sum_f y_f \bar{f} \gamma^5 f, \quad (2.16)$$

$$\mathcal{L} \supset -g_{\text{DM}} Z'_\mu \bar{\chi} \gamma^\mu \chi - \sum_f g_f Z'_\mu \bar{f} \gamma^\mu f, \quad (2.17)$$

$$\mathcal{L} \supset -g_{\text{DM}} Z'_\mu \bar{\chi} \gamma^\mu \gamma_5 \chi - \sum_f g_f Z'_\mu \bar{f} \gamma^\mu \gamma_5 f, \quad (2.18)$$

where y_{DM} denotes the Yukawa coupling between a scalar/pseudo-scalar mediator with the dark matter particle, g_{DM} denotes the coupling of the vector/axial-

vector mediator with χ , S (P) represents a scalar (pseudo-scalar) mediator and Z'_μ a vector or axial-vector mediator, y_f denotes the Yukawa coupling between a scalar/pseudo-scalar mediator with the SM fermions given by $\frac{m_f g_f}{v}$, where v is the Higgs boson vacuum expectation value (VEV) and g_f denotes the coupling of the vector/axial-vector mediator with Standard Model particles. In vector and axial-vector models, the coupling g_f is usually taken to be universal with the distinct types of quarks and leptons, i.e., there is one value of g_q and g_l for all quarks and leptons, respectively.

The interactions observed in the Lagrangian terms above allow for pairs of SM/DM particles to be produced from the collision of SM particles, being mediated by the included bosons. Figure 2.6 shows the Feynman diagrams that are common for each type of mediator. Some particular cases of interest arise when the mediators assume a specific form. In the case of the scalar mediator, it has been proposed that among the invisible decays of the SM Higgs boson that are theoretically calculated to be 0.1% of its branching fraction [58], and has the upper limit experimentally measured of 10.7% [5], a part of its decays could be into DM particles. Another possibility is that it can be a dark Higgs (H_D) [59–61], i.e., a new particle analogous to the Higgs boson that mixes with the SM Higgs, making it possible for the H_D to decay into pairs of SM particles and the standard Higgs boson to decay into pairs of DM particles.

If the mediator is a pseudo-scalar, it can be an axion-like particle (ALP) [62–64]. It has been proposed due to its connection to the strong charge conjugation parity problem in quantum chromodynamics (QCD) [65]. The ALP interacts with the SM via an effective coupling to broaden the new physics that can be studied from this assumption, which can be seen as the parameter Λ in Figure 2.6. Finally, a vector boson can be what is called a dark photon γ_D [66], which can be assumed to mix with either the SM photon and Z boson. Similarly to the H_D case, it is then possible for SM photons to decay into DM particles, and for the dark photon to decay into SM particles. In this particular case, from the DM evidence that was discussed above, the DM particles must have a very small electric charge, usually known as a millicharge, given that its interaction with the SM photon is constrained to be very small [67].

Another example of a simplified model proposes the addition of a complex

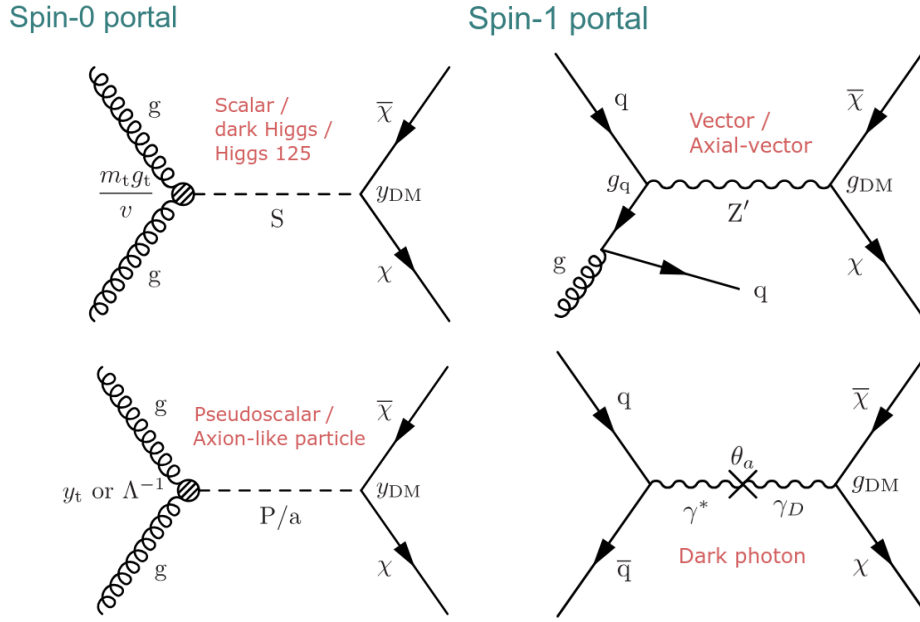


Figure 2.6: Feynman diagrams for distinct types of simplified models. Source: [56]

scalar mediator that directly couples to DM and SM fermions [68, 69]. The interaction term in the Lagrangian is given by the following expression:

$$\mathcal{L}_\Phi = \sum_{i,j} \lambda_{ij} \bar{\chi}_i \Phi_{ij} f_j \quad (2.19)$$

where λ_{ij} are the Yukawa couplings, Φ is the mediator, and the indices i and j are looped over the DM and SM flavors, respectively. Figure 2.7 shows Feynman diagrams of production modes involving the Φ boson.

Even though the simplified models allow for a very large scan of the DM parameter space [70], the interactions described above are only apparently renormalizable, usually violating unitarity constraints [71, 72], leading to nonphysical predictions. The mechanism to adjust these models is to include additional particles in the dark sector (DS) in the so-called extended dark matter models.

2.3.2 Extended Dark Matter Models

The interaction between SM and dark sector particles in more complex DM models works similarly to the above, via portals, but they include more particles in the DS, enriching the dynamics of the model interactions while providing more

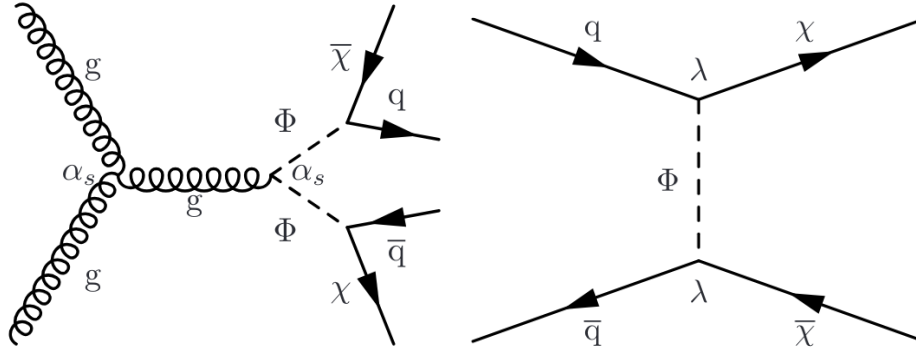


Figure 2.7: Feynman diagrams for some production modes involving the Φ boson: on the left via gluon boson fusion, and on the right a t-channel mediated production of a pair of DM particles. Source: [56]

observables of interest to collider searches. Most of these models are also labeled complete because they are designed not to violate perturbative unitarity and are UV complete. Examples of such models that are searched for in modern particle colliders are the two-Higgs doublet model plus a pseudoscalar (2HDM+a) [73], where the SM-DS interaction is mediated by the added pseudoscalar; inelastic dark matter (IDM) models [74], in which two nearly mass degenerate states are included in the DS allowing for the production of both states in inelastic couplings typically mediated by a dark photon; hidden valleys [75] that add a copy of the SM QCD with a non-Abelian $SU(N_{\text{c, dark}})$ and a broken $U'(1)$ gauge group to include the interaction between the two sectors via a heavy vector portal; and models with supersymmetry (SUSY) [76, 77], where the lightest supersymmetric particle (LSP) is the usual candidate for a dark matter particle.

In short, SUSY is based on the assumption that the SM fields have the so-called supersymmetric partners, which are fields with the spin component changed from half-integer to integer and vice versa. The Standard Model fermions gain scalar partners, the squarks and sleptons, and the Standard Model bosons gain fermionic partners, the gauginos and higgsinos. Similarly to the SM, the SUSY particles acquire mass through a supersymmetry-breaking mechanism, which can be rather different depending on the assumptions made in a given model, and is crucial to explain the absence of SUSY particles being found in modern colliders. Several models can be considered where SUSY is added to the SM such as the minimal supersymmetric SM (MSSM) [78, 79], split SUSY [80], R-parity violating (RPV) SUSY [81], gauge mediated SUSY breaking models [82] and others [83, 84]. In

particular, the focus of this work is on the SUSY model named anomaly-mediated SUSY breaking (AMSB) [85, 86].

Anomaly-Mediated SUSY Breaking

The AMSB model proposes that the SUSY breaking mechanism doesn't couple directly to matter fields. Communicating the effects of SUSY breaking depends on supergravity, where the mechanism to transmit the breaking is via a loop-induced super-Weyl anomaly, which, in practical terms, means that the gaugino masses and sparticle masses squared will be dependent on the mass of the gravitino, $m_{3/2}$.

One issue with the pure AMSB model is that a negative mass squared for the sleptons arises from renormalization, which is solved in the minimal AMSB [87, 88] (mAMSB) by the addition of a term m_0^2 , where m_0 is known as the common scalar mass. In summary, the theory is defined by only four parameters: m_0 , $m_{3/2}$, $\tan(\beta)$ (the Higgs VEVs ratio), and the signal of the Higgsino mass term, $\text{sign}(\mu)$.

The gaugino masses M_1 , M_2 , and M_3 , respectively, the bino, wino, and gluino, at tree level are defined as:

$$M_1 = \frac{33}{5} \frac{g_1^2}{16\pi^2} m_{3/2}, \quad (2.20)$$

$$M_2 = \frac{g_2^2}{16\pi^2} m_{3/2}, \quad (2.21)$$

$$M_3 = -3 \frac{g_3^2}{16\pi^2} m_{3/2}, \quad (2.22)$$

where g_1 , g_2 and g_3 are the $U(1)$, $SU(2)$ and $SU(3)$ gauge coupling constants.

For this work, the most striking feature of this theory is that the masses of the lightest chargino ($\tilde{\chi}_1^\pm$), mixed state of the charged fields of the SUSY partners of SM bosons, and the lightest neutralino ($\tilde{\chi}_1^0$), mixed state of the neutral fields of the SUSY partners of SM bosons, are nearly-degenerate, usually on the order of the Standard Model pion mass $\mathcal{O}(100 \text{ MeV})$. Following the notation in Ref. [87], the mass splitting between these two particles is given by:

$$\Delta_{\tilde{\chi}} \equiv m_{\tilde{\chi}_1^\pm} - m_{\tilde{\chi}_1^0} = \frac{\alpha M_2}{\pi \sin^2 \theta_W} \left[f \left(m_W^2 / M_2^2 \right) - \cos^2 \theta_W f \left(m_Z^2 / M_2^2 \right) \right], \quad (2.23)$$

where α is the fine-structure constant, θ_W is the weak mixing angle, M_2 is defined in Equation 2.21 above, m_Z and m_W are the SM Z and W bosons' mass, respectively, and $f(x)$ is:

$$f(x) \equiv -\frac{x}{4} + \frac{x^2}{8} \ln x + \frac{1}{2} \left(1 + \frac{x}{2}\right) \sqrt{4x - x^2} \left[\arctan \frac{2-x}{\sqrt{4x-x^2}} - \arctan \frac{x}{\sqrt{4x-x^2}} \right]. \quad (2.24)$$

The mass difference, in the limit where $M_2 \rightarrow \infty$, can be reduced to [87]:

$$\Delta_{\tilde{\chi}} = \frac{\alpha m_W}{2(1 + \cos\theta_W)} \left[1 - \frac{3}{8\cos\theta_W} \frac{m_W^2}{M_2^2} + \mathcal{O}\left(\frac{m_W^3}{M_2^3}\right) \right], \quad (2.25)$$

that asymptotically tends to $\Delta_{\tilde{\chi}} = \frac{\alpha m_W}{2(1 + \cos\theta_W)} \simeq 165$ MeV.

Moreover, the very small mass splitting acts as a constraint in the decay of the chargino. This feature implies the possibility of the chargino traveling a substantial distance after its production, giving rise to visible effects in modern particle detectors. The average distance traveled by the chargino in this scenario is [86]:

$$L = \left(\frac{\text{GeV}}{m_{\tilde{\chi}_1^\pm} - m_{\tilde{\chi}_1^0}} \right)^5 \left(\frac{E^2}{m_{\tilde{\chi}_1^\pm}^2} - 1 \right)^{1/2} \times 10^{-2} \text{ cm}, \quad (2.26)$$

where E is the energy of the chargino. It is possible to find that, using $\Delta_{\tilde{\chi}} = 140$ MeV ($\sim m_\pi$) and $E = 2m_{\tilde{\chi}^\pm}$, L is ~ 3.2 m. Also, a mass difference of the order of the pion mass allows for the following chargino decays [89]:

$$\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^\pm, \quad (2.27)$$

$$\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 e^\pm \nu, \quad (2.28)$$

$$\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \mu^\pm \nu, \quad (2.29)$$

which will be of interest for the main goal of this work discussed in Chapter 4.

Since this model is assumed to conserve R-parity, that is, the $U_R(1)$ symmetry between the SM and SUSY fields is not violated, the so-called lightest supersymmetric particle (LSP) has to be stable, given that a supersymmetric particle cannot decay into SM particles only. Conveniently, in the AMSB, the LSP is the neutralino, which makes for a very appealing DM candidate, since it doesn't have electric or strong charges and can be rather massive. A deeper look into the phenomenology

of $\tilde{\chi}_1^0$ being a dark matter candidate is performed in Ref. [88].

Often, extended dark sector models exhibit more interesting signatures to be searched for in particle colliders. However, there are several ways that dark matter particles are indirectly probed, even when considering the simplest extensions to the SM.

2.4 Dark Matter Searches in Particle Colliders

Distinct dark matter models are studied at modern particle detectors with the most varied signatures. However, given the small interaction between DM and SM, these particles are not directly observed by particle detectors, so the detection relies on the missing transverse momentum p_T^{miss} , calculated as:

$$p_T^{\text{miss}} = |\vec{p}_T^{\text{miss}}| = \left| - \sum_i^{\text{visible}} \vec{p}_T^i \right|. \quad (2.30)$$

Therefore, to be observed, the dark matter particle should be produced in association with some visible object, such as SM leptons, hadronic jets⁴, or a SM boson, such as a Z or Higgs boson, that will subsequently decay. These searches usually focus on finding deviations in the p_T^{miss} distribution when compared to the SM predictions.

An alternative approach, instead of using the missing transverse momentum, is to search for new mediators that interact both with SM particles and the dark matter particles by looking at their decay into Standard Model particles, especially in the case where these mediators are assumed to be heavier than SM mediators. In most cases, these searches try to find unexplained localized excesses in the mass distribution of pairs of hadronic jets or leptons.

Furthermore, most of these signatures can be split into those that have the dark sector particle decaying promptly and non-promptly.

⁴Collection of hadronic particles collimated in a given region of the particle detectors.

2.4.1 Promptly Decaying Particles

The most commonly explored models are those where most of the dark sector particles (except for the DM particle) decay promptly after the collision, that is, the region in the particle detectors where the particles are produced is near the particles interaction point, and mainly probe the existence of the DM particle in association with X , which stands for any visible final state object. Apart from the $p_T^{\text{miss}} + X$ signature, DM particles are also studied by searching for the decay products of BSM particles, such as new mediator bosons, supersymmetric particles, and others, that are predicted in models that contain a dark matter candidate.

Taking the CMS collaboration [90] of the LHC [91] as an example⁵, there is a vast program of searches for promptly decaying dark sector particles. From the simplified models, e.g., with searches for spin-0 and -1 and fermionic mediators, all the way up to more complex models such as SUSY-related, UV complete two Higgs doublet models, and many others.

Currently, there is no evidence that a DM candidate was produced in a particle collider, however, an important aspect of these searches in particle colliders is that they are complementary to other detection methods, and it is quite straightforward to extract limits and compare them. Figure 2.8 shows an example of such a comparison, where the latest results for CMS searches in the context of simplified models are converted to the same observables as DDet experiments and the results are displayed in terms of the DM particle mass and the spin-independent (SI) DM-nucleon scattering cross section. Notice that, given the lack of sensitivity of DDet experiments to masses smaller than ~ 3 GeV, the limits from the particle collision experiment are better in that region. An extensive report about the complementarity of collider searches with direct and indirect detections, while also taking into account constraints of DM from astrophysics and cosmology, can be found in Ref. [56].

Most commonly, the particle collider searches focus on a few of the dark sector particle parameters, mainly their masses and couplings to DM and SM. However, it is possible to explore another important characteristic of these particles, without

⁵In the LHC, most of the experiments cooperate in the search for DM evidence [92–94]. In particular, the ATLAS collaboration performs very similar searches as the CMS, intending to find a DM candidate produced by particle collisions.

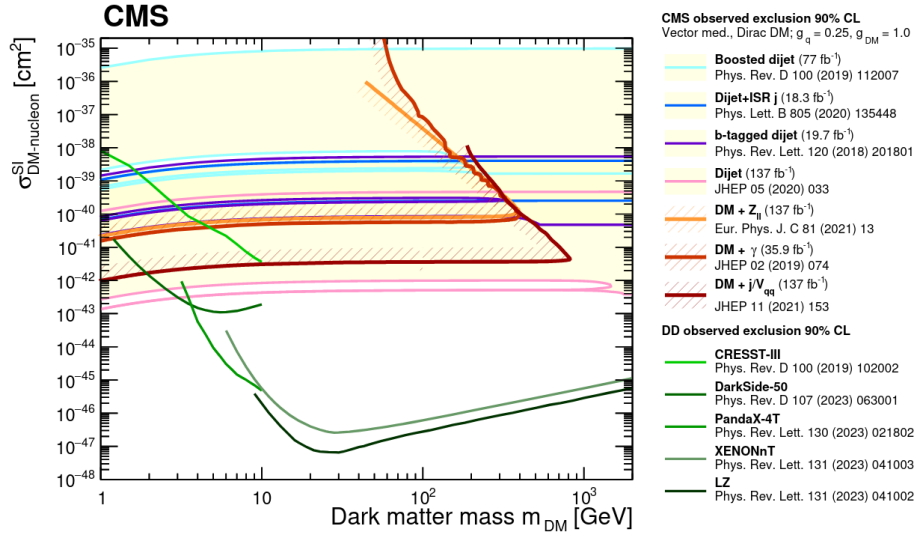


Figure 2.8: Comparison of CMS and direct detection experiments exclusion limits in the plane $m_{DM} - \sigma^{SI}$. The limits are extracted with 90% CL. CMS searches for simplified DM models are translated into DDet observables and are compared with limits from the CRESST-III [43], DarkSide-50 [41], PandaX-4T [42], XENONnT [39], and LZ [40] experiments. Source: [56].

loss of sensitivity by the particle colliders, which is their lifetime.

2.4.2 Long-Lived Particles

Considering the lifetime of BSM particles opens up a new dimension in the parameter space to search for DM evidence in particle colliders. Given that the searches for promptly decaying DS particles were becoming saturated, i.e., the limits on the invariant mass of dijet/dilepton and even SUSY-related signatures reaching values of the same order of magnitude as the highest center of mass energy achieved by particle colliders, a paradigm shift was needed.

Particles with lifetimes large enough to be seen in particle detectors are named long-lived particles (LLP). Dark sector LLPs can generate a myriad of distinct signatures in a particle collider, depending on the type of model and the properties and interactions of these particles with the Standard Model. Figure 2.9 shows some of these different signals. Modern particle colliders are built in layers to measure distinct properties of SM particles (more about this in Chapter 3). The distinct layers can be used to detect LLPs depending on their lifetime, i.e., where they decay in the detector, and their decay products.

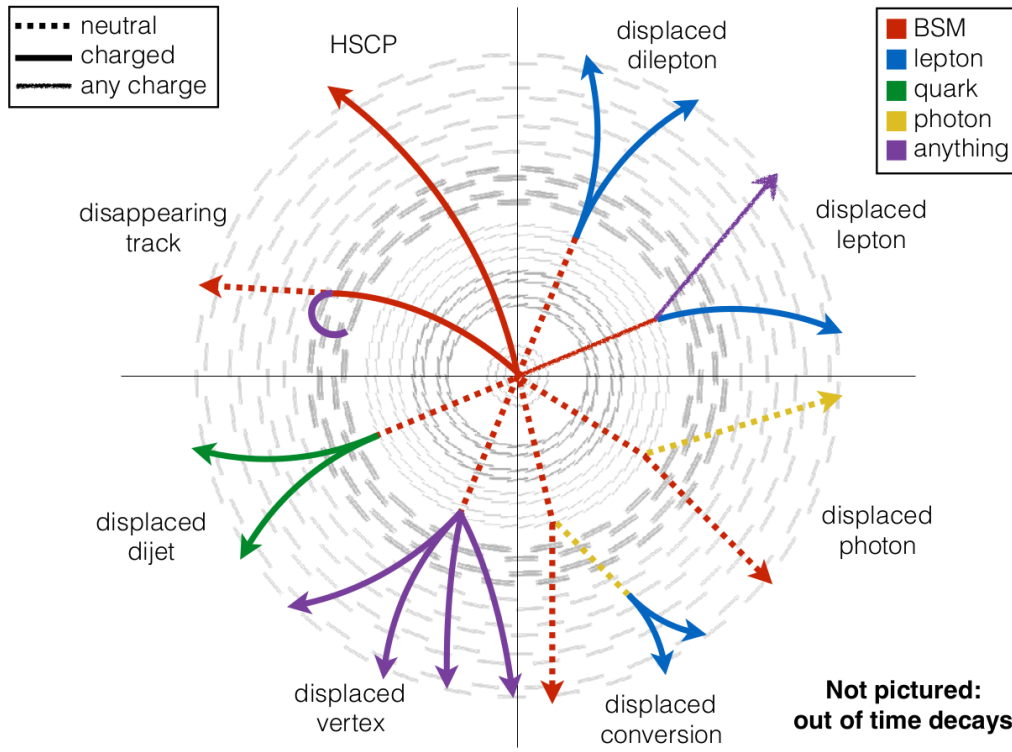
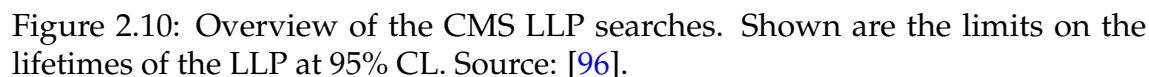


Figure 2.9: Distinct signatures for dark sector LLPs that are explored in CMS. Source: [95].

To showcase the richness of including this observable in searches for BSM models, Figure 2.10 displays the current limits of LLP searches performed by the CMS collaboration [96] at 95% confidence level (CL). Typically, the lifetime of an LLP is measured in terms of $c\tau$, where c is the speed of light in vacuum and τ is its proper lifetime. The choice of using $c\tau$ is because it is easier to relate this quantity to the size of the detector and the particle's decay length. The decay length is what is effectively measured in the particle detector, defined as the geometrical distance between the LLP production and decay points.

In this work, the signature of interest is that of a disappearing track, a charged LLP that "disappears" inside a charged particle tracker, which will be studied in Chapter 4. In the AMSB model this signature is produced by the long-lived chargino, described in Section 2.3.2. Before that, a description of the CMS detector, the modern particle detector used to collect the data for this work, is needed to understand the interactions of the disappearing tracks with the detector.



Chapter 3

The CMS Experiment

The advancement of particle accelerators was of utmost importance to explore elementary particles and their interactions. Most of the particles in the standard model were discovered using these devices. It was not only essential to reach increasingly higher energies to generate more massive particles but also to design particle detectors capable of identifying, reconstructing, and analyzing particles produced in high-energy collisions within a practical time frame.

The world's largest particle accelerator is currently located at the European Organization for Nuclear Research (CERN). The Large Hadron Collider (LHC) [91] is a high-energy particle collision ring with a circumference of 27 km. The data taking is divided into periods of a few years each, called Runs. Currently, the experiment is going through Run 3, which started in 2022 and is planned to finish in the middle of 2026. In Run 3 proton-proton (pp) collisions, the highest center-of-mass energy reached to date is $\sqrt{s} = 13.6$ TeV, while reaching a maximum instantaneous luminosity of $\sim 2 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ using beams of up to 2464 bunches, each containing approximately 1.2×10^{11} protons.

Particles are accelerated with the help of eight radio frequency superconducting cavities (per beam), providing 2 MV of accelerating voltage per particle per passage. With a revolution frequency of about 11245 Hz, this results in 0.18 TeV/s, theoretically requiring only 33.3 s to reach 13 TeV in pp collisions. However, in practice, the process takes approximately 20 minutes because maintaining a tightly focused beam is more critical than achieving maximum energy, and not all of the 2 MV fully impacts the protons.

The LHC's ring comprises 1232 main dipoles, cooled to roughly 2 K, enabling them to act as superconductors and generate magnetic fields exceeding 8 T to bend the particle beams. Additionally, 392 main quadrupoles focus the beams, while nearly 8000 auxiliary magnets are used for beam corrections (also maintained at $\sim$

2 K).

Besides the powerful magnets used to direct particle trajectories and focus the bunches, an exceptionally efficient vacuum system (referred to as the beam vacuum) is required to clear the beam pipe for their passage. In the absence of leaks and under cryogenic conditions, the pressure stabilizes at approximately 10^{-6} mbar, which is about $\sim 10^{-9}$ times atmospheric pressure.

During the so-called third long shutdown (a period that will last from the middle of 2026 until ~ 2029), the machine will be upgraded to the high-luminosity LHC (HL-LHC) [97], a stage where the instantaneous luminosity is estimated to reach up to $7.5 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$, which poses complex challenges to be overcome by its experiments.

The LHC hosts four primary experiments: ALICE (A Large Ion Collider Experiment) [98], ATLAS (A Toroidal LHC AparatuS) [99], CMS (Compact Muon Solenoid) [90], and LHCb (Large Hadron Collider beauty) [100]. LHCb and ALICE are specialized detectors, designed for the study of B hadrons physics and heavy-ion collisions, respectively. ATLAS and CMS are versatile detectors capable of detecting all SM particles either directly or indirectly, also called general-purpose detectors.

The CMS [90] is a general-purpose, cylindrical detector with a diameter of 15 m and a length of 21 m, capable of producing a constant magnetic field of 3.8 T at its center. It weighs approximately 14000 tons, primarily due to the massive field return yokes required to manage the return of the extremely strong magnetic field.

The construction of the CMS detector was designed with a focus on ensuring the subdetectors could withstand extreme operating conditions, such as the intense uniform magnetic field, the high radiation levels, and optimizing the cost-effectiveness of each subdetector. These harsh conditions are particularly true, not only because of the very high rate of bunch crossings of 40 MHz but also because the pileup (PU), i.e., the number of concurrent proton-proton collisions per bunch crossing, can reach up to an average of ~ 60 .

CMS consists of four primary subdetectors: the charged particle tracker (here-

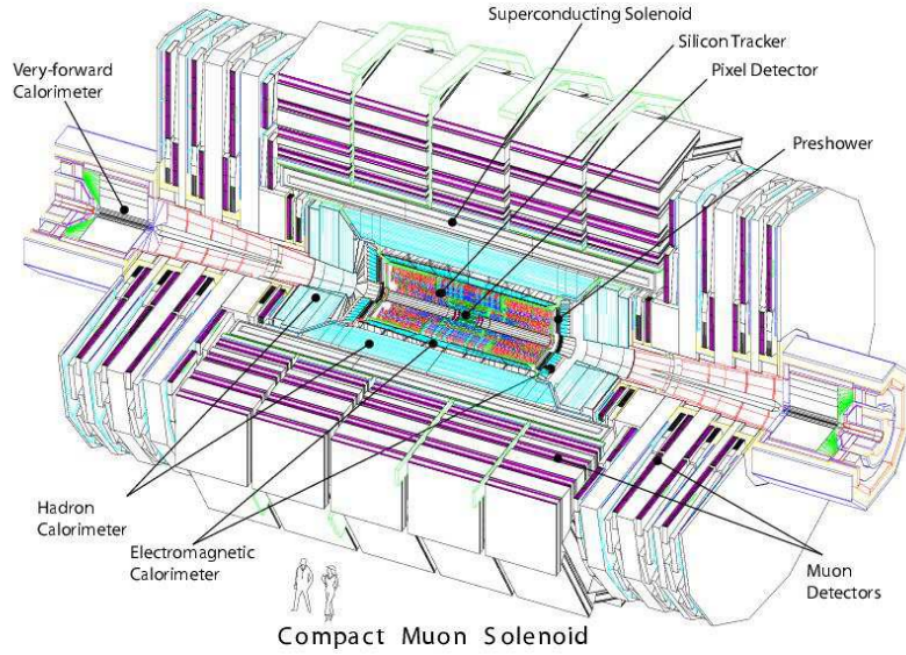


Figure 3.1: Scheme of the CMS detector showing each of its subdetectors. Source [101].

after referred to only as tracker), the electromagnetic (ECAL) and hadronic (HCAL) calorimeters, and the muon system. Each subdetector serves a specific purpose and was developed with an emphasis on achieving excellence in data collection and precision. Figure 3.1 shows a schematic of the CMS detector, highlighting some of its subdetectors along with the superconducting solenoid.

Following the LHC schedule, the experiment went through upgrades to improve the performance of its subdetectors. More notably, the Phase-I upgrade [102–105] that happened during the first and second long shutdowns, in which several modifications were implemented in, essentially, every subsystem of the detector. However, to be able to withstand the high luminosity environment of the HL-LHC upgrade, the Phase-II upgrade [106–114] is foreseen to take place during the third long shutdown.

3.1 Tracker

The tracker (Figure 3.2), as its name suggests, is a silicon-based detector designed to track the trajectory of charged particles. It is further divided into two

subsections: the inner tracker, which uses silicon pixels, and the outer tracker, which relies on silicon microstrips. Both subsections operate on the same detection principle: a bias voltage is applied to a doped silicon sensor so that, when a charged particle passes through the material, it generates electron-hole pairs that are attracted to the cathode and anode, respectively, producing an electric current that can be measured.

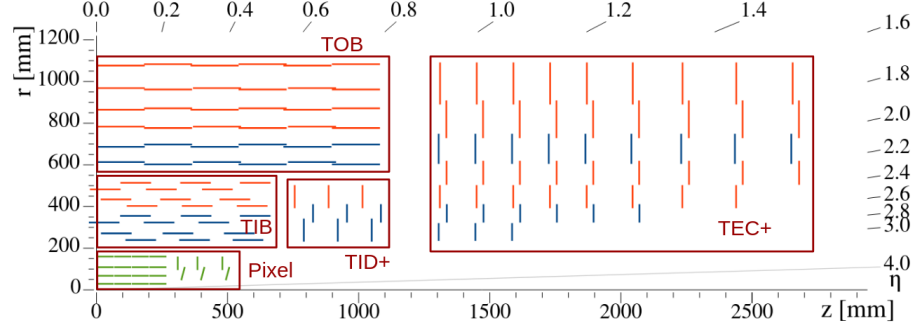


Figure 3.2: A quarter of the CMS detector tracker sketch, showing the sections of the pixels and strips. Mono and stereo strip modules are shown as red and blue lines, respectively. Source [107] (modified).

The division into two subsections arises from the need for high granularity in the region closest to the interaction point (IP), where the IP is the physical point where the pp collisions happen inside the beam pipe. This ensures greater accuracy in reconstructing the characteristics of charged particles and vertices, regions where more than one charged particle originated, while also optimizing material costs.

The pixel detector is divided into three regions surrounding the IP: the barrel (BPix), which consists of four concentric cylinders aligned with the z and $r - \phi$ axes relative to the IP (located at the origin of the r, ϕ, z coordinate system), and the two endcaps (FPix), which are the "lids" of the detector, three concentric disks on each side of the detector positioned at defined distances along the z -axis. The pixel region provides coverage for a pseudo-rapidity of $|\eta| < 2.5$.

Each pixel has dimensions of $100 \mu\text{m} \times 150 \mu\text{m}$ and a thickness of 285 (300) μm for barrel (endcap) pixels. This configuration ensures a spatial resolution of $10 - 40 \mu\text{m}$ depending on the axis being considered. Silicon was chosen due to its manufacturing allowing for high granularity, strong resistance to radiation,

excellent performance in high magnetic field regions (especially in the endcaps, where the solenoid's magnetic field is non-uniform), and its ease of manipulation at the microscopic scale by the industry.

For strips, there are four regions surrounding the IP and the pixel detector: the inner barrel (TIB; 4 concentric cylinders), the inner disks (TID; 3 concentric disks on each side of the detector, symmetrically positioned about $z = 0$), the outer barrel (TOB; 6 concentric cylinders), and the endcaps (TEC; 9 concentric disks on each side of the detector).

Since this subsection does not require such a high granularity (thanks to the pixel detector), and material cost efficiency is also important, micro-strips are used. These are silicon bands for detecting charged particles, with dimensions of $10 \text{ cm} \times 80 \text{ }\mu\text{m}$ in the inner region and $25 \text{ cm} \times 180 \text{ }\mu\text{m}$ in the outer region. This subsection also covers a pseudo-rapidity of $|\eta| < 2.5$.

Additionally, the tracker as a whole must maintain precise temperature control to optimize the performance of silicon sensors and electronic components, ensure high spatial measurement resolution (to counteract dimensional changes in the subdetector caused by temperature variations), and mitigate the effects of radiation on its components. The tracker sensors are operated at $\sim -20^\circ\text{C}$.

3.2 Electromagnetic Calorimeter

The second subdetector is the ECAL (Figure 3.3), which is responsible for measuring the energy of electrons, positrons, and photons that get to it. An electromagnetic calorimeter must have a high capacity for electromagnetic interaction, strong resistance to radiation, precise measurement accuracy to determine the energy of incident particles, and a fast response time. Specifically, the ECAL also requires excellent performance in the 3.8 T magnetic field region, as it operates within the CMS solenoid.

The ECAL is composed of approximately 80,000 PbWO_4 crystals, which have a high density of 8.28 g/cm^3 and a radiation length, X_0 , of 8.9 mm, with a Molière radius of 22 mm. This means that electromagnetic particle showers will be mostly contained within this region. The crystals are resistant to radiation and, even

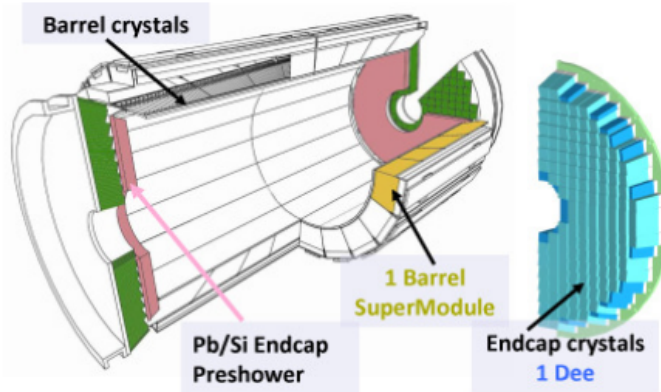


Figure 3.3: Scheme of the ECAL subdetector. Modules of crystals are assembled and then allocated in the barrel and endcaps. The CMS preshower detector is also shown. Source [115].

though they may darken due to prolonged radiation exposure, this effect can be calibrated. Additionally, the crystals have a scintillation time of approximately 25 ns, which remains unaffected by the darkening. A key feature of these crystals is that they are transparent to their scintillation light.

The measurement of photons and electrons (positrons) energy is based on the scintillation of these crystals. When a charged particle, such as an electron (positron), interacts with the medium, electromagnetic interaction processes like Bremsstrahlung, Cherenkov radiation, Möller scattering, etc., produce a photon and another electron (positron), which then interacts again, generating several other particles. For photons, processes like electron-positron pair production, Compton scattering, and the photoelectric effect lead to a shower of particles. The intensity of the signal produced by this particle shower is proportional to the energy of the incident particle.

The ECAL crystals are divided into two regions: the barrel (EB), where the crystals are arranged radially relative to the IP, with a specific inclination depending on the pseudo-rapidity, and the endcaps (EE), where the crystals closest to the IP (high pseudo-rapidity) are almost parallel to the beam axis, while those further away (as pseudo-rapidity decreases) are angled relative to the z -axis, depending on $|\eta|$. The barrel covers the region $|\eta| < 1.479$ and consists of trapezoidal crystals, 230 mm long (corresponding to $25.8 X_0$), with faces measuring $22 \times 22 \text{ mm}^2$ at the IP side and $26 \times 26 \text{ mm}^2$ at the far side. The endcaps cover the region

$1.479 < |\eta| < 3.0$, with crystals of the same shape as the barrel but 220 mm in length (corresponding to $24.7 X_0$), and with the faces closest and farthest from the IP measuring $28.62 \times 28.62 \text{ mm}^2$ and $30 \times 30 \text{ mm}^2$, respectively.

In the barrel, an avalanche photodiode is placed on the side of the crystal farthest from the IP. This device absorbs the particles produced by the interaction of the incident particle, converts the pulse into an electrical signal, amplifies the signal, and sends it for analysis. In the endcaps, due to the high inhomogeneity of the magnetic field, vacuum phototriodes are used for this function, as they perform well under such conditions.

Additionally, the CMS preshower detector is part of the ECAL. Located in the endcaps, this detector covers the region $1.653 < |\eta| < 2.6$ and is designed to detect neutral pions, whose most likely decay product is two photons.

For ECAL, temperature control is also crucial. The gain of photodiodes and phototriodes is temperature-dependent, and small temperature fluctuations can lead to significant variations in the measured energy. To optimize the resolution of the subdetector, the temperature must be maintained at $(18.00 \pm 0.05) ^\circ\text{C}$.

3.3 Hadronic Calorimeter

The HCAL (Figure 3.4) is divided into four regions: the barrel (HB), the endcaps (HE), the outer calorimeter (HO), and the forward calorimeter (HF). Each of these regions is designed to measure the energy deposited by hadronic jets, with the primary differences being their locations and the types of absorbing and active media used (such as the higher radiation levels received by the HF, for instance).

The regions consist of an absorbing medium (brass and steel plates) and an active medium (plastic scintillators in the case of HB and HO, and quartz-based scintillators in the case of HEs and HFs) combined. Steel plates form the first and last components of each region, with brass plates and the corresponding active medium placed between them. For example, in HB, from the plate closest to the IP to the furthest, the structure includes: a 40 mm thick steel plate, 14 brass plates with thicknesses of 50.5 mm for the first eight and 56.5 mm for the last six, with the active medium (plastic scintillator) between them, followed by another steel

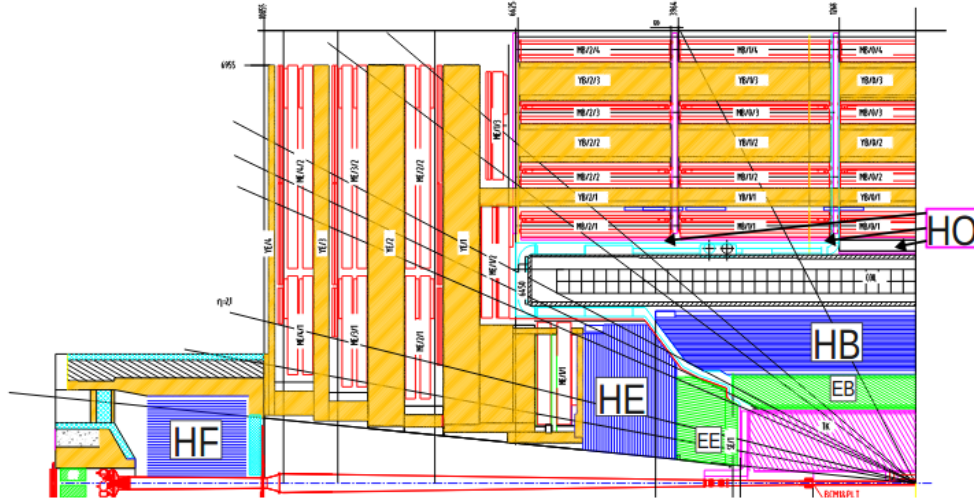


Figure 3.4: Scheme of the HCAL and its sections. The colors indicate the CMS subdetectors (pink for the tracker, green for ECAL, blue for the HCAL regions, and red and orange for the muon system). Source [116].

plate that is 75 mm thick.

The absorbing medium ensures that incident hadrons interact within the detector (approximately ten interaction lengths, λ_I , in all HCAL regions), generating a shower of hadronic and electromagnetic particles. These particles, upon interacting with the active medium, emit a brief light pulse (either fluorescence or Cherenkov light, depending on the active medium), which is detected by photo-sensitive devices called hybrid photodiodes (replaced by silicon photomultipliers in the Phase 1 Upgrade of the HCAL [104]). Similar to the ECAL, the intensity of the detected signal is proportional to the energy of the incident particle.

Each HCAL region is designed to cover different pseudo-rapidity values, which dictate the choice of absorbing and active media. The greater the pseudo-rapidity, the higher the incident radiation on the HCAL components. Additionally, in the high $|\eta|$ regions, the magnetic field becomes highly non-uniform. Therefore, specific brass alloys and quartz scintillators are used in HFs and HEs, as they are more resistant to radiation, unlike plastic scintillators, which have a lower tolerance. These materials are also capable of operating without significant influence from the magnetic field. All HCAL regions cover a total pseudo-rapidity range of $|\eta| < 5$, with HB covering $|\eta| < 1.3$, HO also covering $|\eta| < 1.3$, HEs extending from $1.3 < |\eta| < 3$, and HFs spanning $3 < |\eta| < 5$ (which experience very high

incident radiation).

In the region up to $|\eta| = 1.3$, EB and HB alone are insufficient to detect all the hadronic jets, i.e., the interaction length is not enough to stop all objects, necessitating the development of another calorimeter to capture these jets. The HO is positioned after the first iron wall, which is essential for the return of the magnetic field. This wall aids in the containment of hadrons and the formation of showers that will be detected by the HO.

The calorimetry system (ECAL + HCAL) was designed to capture almost every product of a particle collision, except for muons and neutrinos, and to be hermetic, meaning it covers as much of the area around the IP as possible.

3.4 Muons System

The CMS experiment was specifically designed to detect events involving muons using a separate spectrometer. Since it is positioned after the calorimeters, it is expected that only muons will leave detectable traces in this subdetector. The CMS muon detection system (Figure 3.5, which already takes into account the Run 3 and Phase-II upgrades with the addition of the ME0, iRPCs, and GEMs [111]) needs to have a fast response time, a high capability to detect, identify, and track muon trajectories and vertices, while also providing precise measurements of muon momentum. Additionally, due to its large active detection area (approximately $28,000 \text{ m}^2$), the components should be cost-effective, yet highly reliable.

The muon system is composed of four types of detectors, all based on similar detection principles: drift tubes (DT), which provide high-resolution position measurements; cathode strip chambers (CSC), which measure the position of charged particles and can operate in regions with strong and non-uniform magnetic fields; resistive plate chambers (RPC), which are capable of recognizing muon events at very high rates (faster than 25 ns); and gas electron multipliers (GEM), that were installed during the second long shutdown, and were developed to provide efficient measurements even in the higher radiation section of higher η . By utilizing all four systems, it is possible to quickly and accurately identify muon events and measure their position and momentum, even in the harsh environment of the upgraded LHC during Run 3.

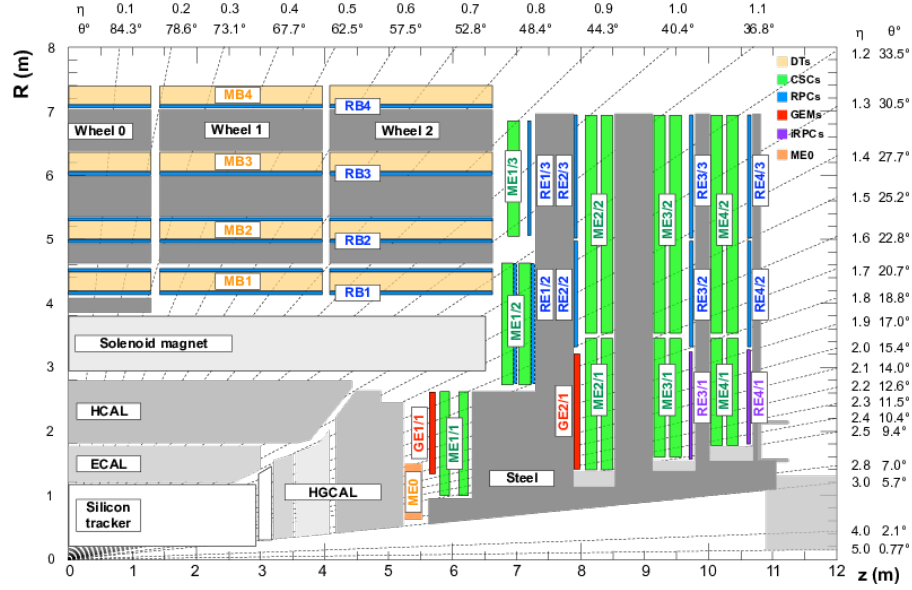


Figure 3.5: View of a quarter of the muon detection system. The types of detectors are separated by color: DTs - yellow; CSCs - green; RPCs - blue; GEMs - red; ME0 - orange; and iRPCs - purple. The last three are part of the Phase-II upgrade but had testing modules installed for checks in Run 3. Length, radius, and some pseudo-rapidity values are also indicated. Source [117].

An important note is that the iRPCs are a type of RPCs that were designed to improve the coverage of the muon system without loss of efficiency and to be able to cope with the more radiation-affected region of the detector. Up until now, a few modules of the GEMs and iRPCs were installed for studies, with the full capability of these subsystems to be explored during Phase-II of the CMS detector.

The detection of muons is carried out by the four types of detectors as follows: a specific gas mixture (which varies for each type) is ionized when a muon passes through with energy greater than or equal to that of a minimum ionizing particle (MIP). High and precise potential differences are applied to the cathodes and anodes to generate an electric field (in some cases, electrodes are also used to contain this field and prevent electrical discharges), causing positive ions to be attracted to the cathode and electrons to be drawn to the anode, producing an electrical signal that can identify muon events and measure their position.

All systems exhibit subtle differences, including variations in granularity and

assembly methods. For example, the RPCs were designed with a double-chamber detection system, optimizing their performance at the required high rates.

DTs and RPCs are arranged around the IP, aligned parallel to the beam in barrel formations, while CSCs are positioned like the endcaps of the detector, and GEMs/iRPCs are included to increase the pseudorapidity of the muon detection. DTs cover a region of $|\eta| < 1.2$; the CSCs span $0.9 < |\eta| < 2.4$; RPCs cover $|\eta| < 1.9$; and GEMs and iRPCs span $1.5 < |\eta| < 2.8$, providing high-resolution muon detection across nearly all solid angle.

3.5 The Trigger System

In the CMS experiment, the first stage where events are selected is called the trigger [118]. Normally, the beams in the LHC cross at a rate of 40 MHz, and depending on the instantaneous luminosity, more than one proton-proton (pp) collision can occur during each crossing. Due to the vast amount of data produced by these collisions, not all data can be read out or stored, and therefore, some selection must take place. The trigger system was designed to select only the most relevant events from the total data produced, while being able to sustain the high rate of LHC collisions, i.e., its decision must be computed in a short amount of time.

The trigger system is divided into two stages: the Level 1 Trigger (L1T) [119] and the High-Level Trigger (HLT) [120]. The L1T is a set of physics object-based selections applied via field programmable gate arrays (FPGAs; hardware) directly to the detector, where the data is collected after an event, and the L1T immediately begins processing. The L1T was designed to reduce the 40 MHz event rate to around 100 kHz and process each event in at most 4 microseconds.

Selections are made by identifying candidates for electrons/photons (e/γ) and jets, using information from the ECAL and HCAL, and muon candidates from the muon system. For the e/γ candidates, a variable associated with their isolation is calculated, and the muon candidates undergo a track-finding algorithm at this stage. The output of the trigger for events that pass the selection includes candidate information and several global variables. Different selections can be made at this stage depending on the type of physics being studied.

Given the large volume of events that need to be efficiently selected by the L1T in Run 3, new algorithmic approaches were included in the classification of events [121], which are based on machine learning (ML) techniques. These ML algorithms are implemented in FPGAs via a facilitator software named HLS4ML [122]. Also, improvements planned for Run 3 within the L1T primarily aim to extend the physics capabilities of CMS. This is being achieved by introducing specialized triggers for LLP signatures, refining objects reconstruction and calibration, using the upgraded calorimeter trigger primitives¹ (TPs) and additional muon TPs provided by the new GEM muon detector, and incorporating further computations within the global trigger² (GT) to enable a more versatile L1 trigger algorithm design. For the LLP signatures, the TPs contain accurate timing information from the distinct subdetectors, allowing for precise measurements of the time of flight of the reconstructed objects.

After the L1 trigger, a large number of events still need to be discarded, requiring a second selection stage. The HLT is performed by computer algorithms (software) after the L1T selections. The goal of the HLT is to further reduce the event rate from ~ 100 kHz to a few kHz. The HLT runs on a commodity computer farm and is implemented with a dedicated configuration of the CMS reconstruction and analysis software (CMSSW) [123] that is also used for offline processing. The HLT configuration, called “menu”, is composed of hundreds of event selection “paths” running in parallel. Each path implements a different event selection algorithm, written as a set of C++ self-contained modules, specialized to reconstruct and select events based on a specific final state. In Run 3 the HLT menu is designed to select events with an average rate of ~ 2 kHz, with an average processing time smaller than 500 ms. Due to the modular nature of CMSSW, the event reconstruction is shared by the various paths and is performed only as needed, starting from the simpler operations, taking $\mathcal{O}(10\text{--}100)$ ms to complete, up to the more complex objects reconstruction and selection that can last for $\mathcal{O}(100\text{--}1000)$ ms). The shape of the HLT timing distribution is shown in Fig. 3.6 for a Run 2 menu, where it is possible to see different structures arising due to the complexity of distinct paths. For Run 3, the HLT computing farm was upgraded, where the event processing is carried out by 25,600 central processing unit (CPU)

¹Trigger primitives are objects that come from a small resolution readout of the CMS detector.

²The global trigger gives the final decision of the L1T, if the event is accepted or not based on its characteristics.

cores and 400 graphics processing unit (GPU) cards. As with the L1T, various selection algorithms are applied depending on the events of interest being targeted.

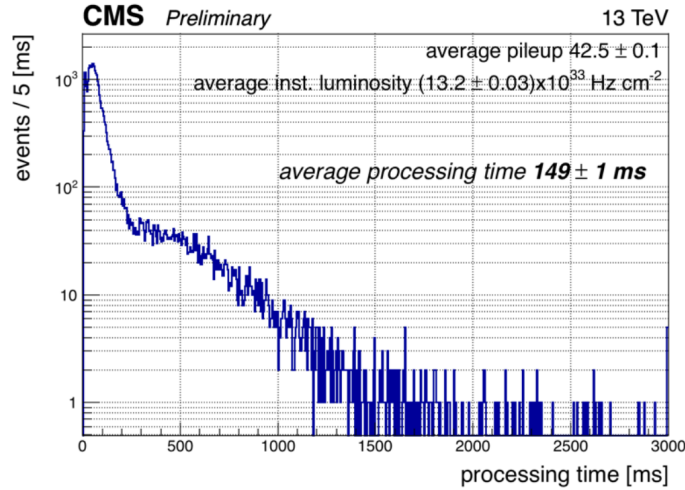


Figure 3.6: HLT menu timing measurement using a 2016 run as an example. Three distinct structures can be seen in the shape of the distribution: a peak around 20 ms related to events that pass or fail the HLT selection based on L1T, calorimeter or standalone muon information; a peak around 100 ms related to events that are accepted or rejected based on pixel or global muon information or the electron reconstruction; and a tail that relates to the events that are rejected/accepted based on the full tracking and physics objects reconstruction. Source: [124].

Besides the computational power increase, the HLT events reconstruction also utilizes multithreading to increase the throughput of events and mitigate the consumption of memory per CPU core. A thread is a list of instructions to be executed by the given processor, where CPU architectures are designed to process a smaller number of sequential, and more complex, lists of instructions. Adopted in 2015, the multithreaded CMSSW framework was implemented via Intel’s thread building blocks (TBB) library `oneTBB` [125], which organizes concurrent workloads as tasks and dispatches them using `oneTBB`’s task scheduler. Currently, production jobs are configured to use eight threads by default, balancing memory usage and CPU efficiency effectively.

The earlier version of the multithreaded framework only allowed for the concurrent processing of separate events. Synchronization between worker threads was required at certain stages of data handling, and combined with the significant variation in processing time across collision events, this resulted in some

inefficiency in CPU usage. Over time, threading efficiency has significantly improved [126], and multiple levels of concurrency are now utilized. Within a single event, independent modules, i.e., the algorithms that the framework schedules, are executed in parallel wherever data dependencies allow. Modules can also utilize oneTBB's parallel features in their internal operations, including event setup modules that manage conditions data. The framework accommodates physics modules with varying thread-safety levels, which also influence their efficiency and memory footprint.

Finally, in preparation for Run 3, the HLT software was modified to exploit heterogeneous computing architectures, and many reconstruction modules were developed to make use of these resources to address the challenges posed by increasing luminosity and pileup. Algorithms capable of running on both CPUs and GPUs are automatically scheduled to execute on a GPU when one is available; otherwise, the CPU version is used. GPUs are designed to handle hundreds or thousands of simpler and independent operations in parallel, where the CPU threads are responsible for launching the relevant instructions on the GPU. The threads in the GPUs are usually divided into blocks of threads [127], where the blocks are set in a grid. Each block and thread is assigned an x , y , z index to differentiate each element. Threads executing instructions in parallel in a block can communicate.

These software modifications were based on offloading computations to co-processors and the introduction of faster reconstruction methods, which were indispensable for Run 3 data collection and processing [121]. To give a sense of the amount of speed-up obtained by offloading part of the HLT reconstruction to GPUs, Figure 3.7 shows the comparison of running the HLT event reconstruction with CPU only and the CPU+GPU approach. About 50% faster reconstruction is achieved with CPU+GPU processing.

Even though the usage of CPUs+GPUs to reconstruct events in the HLT decreased the time needed for this task, it introduced a couple of problems: harder maintainability, due to code duplication, and exclusivity to one type of accelerating device, since the reconstruction code was only implemented for GPUs from a single manufacturer (NVIDIA). These issues and the implemented solution to these problems are discussed in Chapter 5.

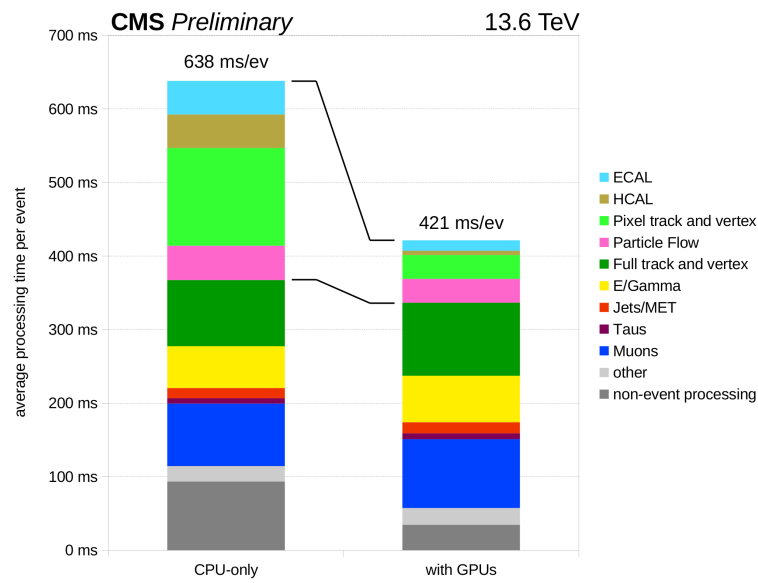


Figure 3.7: HLT processing time comparison when using CPU-only and when offloading part of the HLT processing (ECAL unpacking, HCAL local reconstruction, and PF clustering, and pixel tracks and vertices reconstruction) to GPUs, estimated using 70k collected events with an average PU of 63.7. Source [128].

Chapter 4

The Run-3 Framework for the Disappearing Tracks Search

Disappearing track searches at particle colliders are especially interesting, as no standard model particles can mimic this signature. Figure 4.1 shows the proper lifetime versus mass of SM particles, where it is possible to see that particles with lifetimes on the order of 10^{-11} – 10^{-7} seconds, which can produce measurable tracks that vanish in the CMS tracker, will either decay into visible products, or are electrically neutral. Charged particles with proper lifetimes larger than $\sim 10^{-7}$ s will usually traverse the full tracker, while proper lifetimes smaller than $\sim 10^{-11}$ s imply that the particle will decay before the first layers of the tracker. This chapter explores chargino properties, reviews AMSB searches in the contexts of dark matter and SUSY, and focuses on the disappearing track search using CMS Run 3 data. It also discusses changes in the analysis framework to improve the generation of signal events and to use a more accessible data format, and outlines the triggering strategy for the Run 3 search.

Theoretically, any SM particle either lives long enough to traverse the full tracker or decays promptly enough that only the decay products are seen. An important feature of an unstable particle is that the number of particles is dependent on its lifetime, following the exponential decay rate given by:

$$N(t) = N_0 e^{-t/\tau} \quad (4.1)$$

where $N(t)$ is the number of leftover particles after a time t , N_0 is the number of particles at $t = 0$ and τ is the proper lifetime. This exponential decay gives rise to tracks of different sizes for the same proper lifetime. Figure 4.2 shows the distinct decay lengths and $c\tau$ distributions for a particle with a proper lifetime of 3.336 ns (or $c\tau = 100$ cm). The different decay lengths allow for the data analyses to search for multiple-sized tracks and explore the sensitivity of the particle detector for

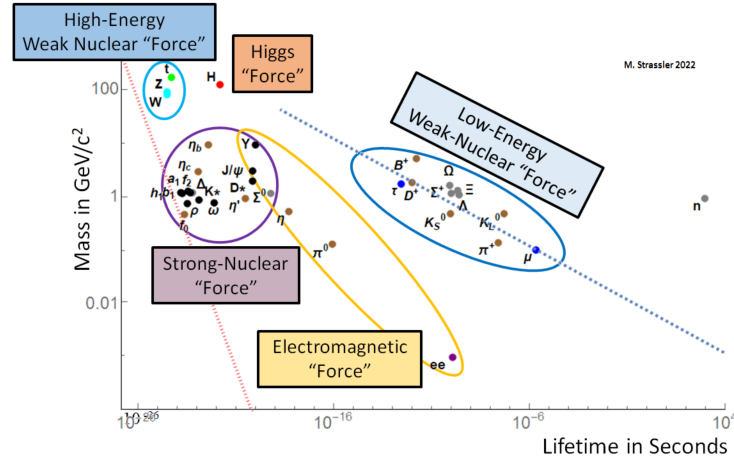


Figure 4.1: Proper lifetime versus mass of the standard model particles. The particles are "clustered" concerning the force that causes the particles to decay, given that the particles' lifetimes and the strength of this force are correlated. Source: [129] (modified).

many cases.

In the context of a dark matter search, the models of interest assume that the charged LLP decays into a very soft (momentum on the order of ~ 100 MeV) SM particle and the DM candidate. Given the very low momentum, the SM particle will most likely not be reconstructed by the CMS detector, and the DM particle will not interact with the detector material, giving the signal of a charged particle that vanishes inside the tracker. This signal is that of a track with a larger number of missing hits in the outer layers of the tracker ($N_{\text{miss}}^{\text{outer hits}}$) and low energy associated with it deposited in the calorimeters (E_{calo}). In summary, hits represent the position of the energy deposits of a charged particle in the tracker layers (defined in more details in Chapter 5), and a missing hit refers to an active tracker layer that should contain a hit, estimated from the charged particle trajectory, but does not (defined in more details in Section 4.3). In the AMSB model, the mass difference between the chargino and the neutralino (described in Section 2.3.2) on the order of the pion mass fits perfectly with the signature of a produced disappearing track, given that it contains a charged LLP decaying into particles that will not be detected by the CMS detector. The production modes of the AMSB chargino rely on the pair

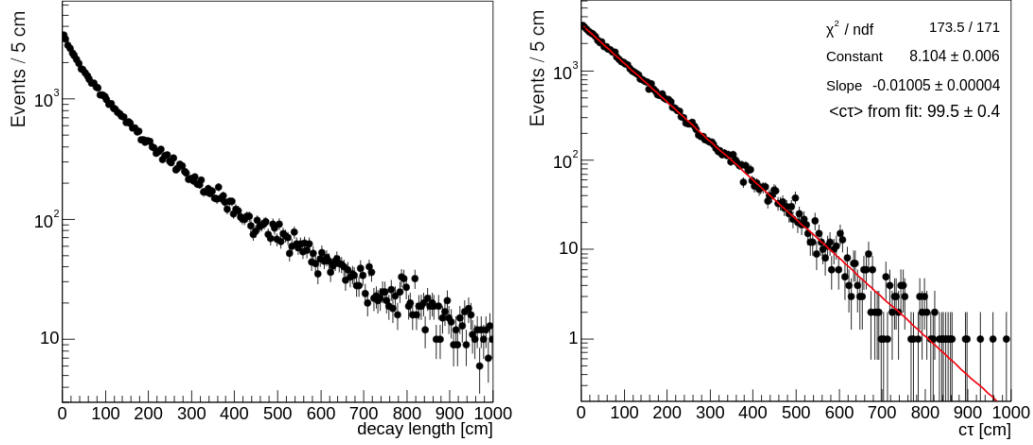


Figure 4.2: Decay length (left) and $c\tau$ (right) for a long-lived particle with a proper lifetime of 100 cm of $c\tau$. In the right figure, the red line comes from an exponential fit of the data with an exponential decay.

production of electroweakinos given by:

$$pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp, \quad (4.2)$$

$$pp \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm. \quad (4.3)$$

Until now, many searches for this type of signature were performed in the context of trying to find evidence for DM [130–138] or supersymmetry [139–142]. As mentioned in Section 2.3.2, the AMSB model is used to benchmark most of these searches, and is the focus of this work. However, several models can also generate a disappearing track signature [143–149].

The latest disappearing tracks search from the CMS collaboration [138] was performed using 101 fb^{-1} of Run 2 pp collision at $\sqrt{s} = 13 \text{ TeV}$ data collected from 2017 and 2018, and found no excess of disappearing tracks when compared with the background-only hypothesis. Because of these results, it was possible to set new limits to the mass and lifetime of the chargino, excluding charginos of mass 884 (474) GeV for a lifetime of 3 (0.2) ns, when combining with the 38.4 fb^{-1} of 2015–2016 data from Ref. [137]. In this search, a second benchmark model was used in the context of SUSY, in which the LSP is the neutral higgsino, hence a DM candidate, that also exhibits a small mass difference ($\mathcal{O}(100 \text{ MeV})$) with the charged higgsino. This is shown to be a general characteristic of models that contain massive vector-like electroweak doublets [150]. Therefore, the chargino,

which will now be explicitly referred to as wino- or higgsino-like depending on the case, is also able to decay into the same final states shown as the processes in Equations 2.27 – 2.29, and is produced following the processes in equations 4.2 – 4.3 above, with the addition that the second lightest higgsino state ($\tilde{\chi}_2^0$) is degenerate in mass with the first, allowing for the $pp \rightarrow \tilde{\chi}_2^0 \tilde{\chi}_1^\pm$ production mode. The latest CMS Run 2 search was able to exclude higgsino-like charginos with a mass of 750 (175) GeV for a lifetime of 3 (0.05) ns (using only 2017–2018 data).

In the Run 3 search, described in this work, some modifications to the analysis procedure were made. Firstly, a change in the method to generate the AMSB signal events for the analysis was performed to reduce the largest systematic uncertainty source of the search. Secondly, the method to measure the calorimeter energy associated with a track was changed to use a more easily accessible proxy variable, implying a faster and more straightforward data analysis.

4.1 Signal Events Simulation with MadGraph

As observed in Ref. [138], the largest source of systematic errors was the initial state radiation (ISR) corrections, where the average value of the uncertainty was 13% across all data periods and chargino masses, lifetimes, and types. Those corrections are related to the capability of the Monte Carlo (MC) generators to accurately model the radiation of extra partons, i.e., quarks and gluons, from the initial interacting partons. The radiated partons hadronize [151], generating a hadronic jet that recoils against the produced pair of electroweakinos. In the disappearing tracks search, it is fundamental that the ISR is modeled as close to what would be expected from data as possible, since the signal can only be triggered if the pair of electroweakinos recoils against a high p_T jet. This occurs because at the Level 1 trigger, there is no reconstruction of tracks from charged particles, and the GT depends only on the calorimeter and muon systems information to make the L1T decision. Given that the charginos do not reach the calorimeters and their decay products are undetected, the pair of produced particles has to recoil against something visible to be selected at the L1T. This is defined in more details in Section 4.3.

In the estimation of the uncertainty two sources were considered: one related to the mismodelling of Z bosons p_T (in this context, the production of a Z boson re-

coiling against a hadronic jet is assumed to be similar to that of a pair of charginos) when comparing MC with data; and the other related to the mismodelling of the ISR p_T when comparing Pythia (PY8) [152] and MadGraph5 (MG5) [153, 154] $Z \rightarrow ll$ process, since Pythia was used to generate the signal MC samples in Run 2. The main issue is that parton shower (PS) generators such as PY8 are known to deviate from better modeling of processes that include extra hard jets in the matrix element (ME) calculation, especially in regions of hard and separated radiated jets due to the lack of subleading terms and interference [155]. However, using MG5, which performs the ME calculation with extra hard partons more accurately, does not completely solve this issue, given that it does not correctly describe the region of soft and collinear radiated partons [155]. The solution comes in the form of the jet matching algorithms [151, 156] that are schemes to correctly account for hard and soft QCD radiation by combining the ME and PS generators, while avoiding the double counting of intersecting events.

Even though many possible jet matching schemes exist [157–160], in this work, the matching scheme known as MLM was used to better account for the effects of ISR. In this method, the final jets resulting from parton-shower evolution and jet clustering are compared to the original partons. An event is accepted if a reasonable correspondence is found; otherwise, it is discarded. This rejection step effectively introduces a Sudakov form factor to the hard processes. Importantly, the parton shower must avoid generating emissions that would duplicate hard activity already accounted for in the matrix-element calculation.

In practice, two energy scales control the merging algorithm that are the minimum p_T of a hard parton and the minimum transverse energy at which hard partons and clusters will be matched, which will be referred to as $x_{Q\text{cut}}$ and q_{cut} . These follow the namings used in MG5 and PY8, respectively. Since the search for disappearing tracks is benchmarked in terms of the mass of the chargino, the values of the $x_{Q\text{cut}}$ and q_{cut} parameters were found for each $m_{\tilde{\chi}_1^\pm}$ following the procedure described in Ref. [155]. The method is based on the smoothness of the differential jet rate (DJR) distribution of the simulated processes, especially in the transition region from distinct multiplicities. The processes of interest simulated¹ with MadGraph5 2.9.9 were:

¹In parallel to this work, a study on the possibility of generating hadronic jets using ML generative algorithms was conducted. Appendix A describes the methods used and the results obtained.

- $pp \rightarrow \chi_1^\pm \chi_1^0$,
- $pp \rightarrow \chi_1^\pm \chi_1^0 j$,
- $pp \rightarrow \chi_1^\pm \chi_2^0$ (for the higgsino-like case only),
- $pp \rightarrow \chi_1^\pm \chi_2^0 j$ (for the higgsino-like case only),
- $pp \rightarrow \chi_1^\pm \chi_1^\pm$,
- $pp \rightarrow \chi_1^\pm \chi_1^\pm j$,

at leading order (LO) with the NNPDF3.1 NNLO [161] parton distribution function (PDF) sets, and the simulation of parton showers, jets merging, and hadronization was performed with Pythia 8.306. To clusterize the partons produced by the shower evolution, the Pythia internal SlowJet routine with the k_T clustering algorithm [162, 163] is used.

Even though MadGraph5 contains the MSSM model included in its framework, and the dynamics of this model with the AMSB model are practically identical, MG5 does not use the correct particles' parameters, which must be estimated externally. As mentioned in Section 2.3.2, the mass spectrum in the AMSB scenario is governed by four parameters: $m_{3/2}$, m_0 , $\tan(\beta)$, and $\text{sign}(\mu)$. Among these, only $m_{3/2}$ significantly affects the mass of the lightest chargino. By varying $m_{3/2}$, the full SUSY mass spectrum is computed using IsaJet 7.80 [164]. The chargino mass is scanned over a range between 100 GeV and 1200 GeV (up to 1000 GeV in the higgsino-like case), in steps of 100 GeV. The specific SUSY parameters used at each mass point are detailed in Table 4.1. Depending on the type of chargino, different decay modes were set for the LLP: in the wino-like case, the chargino has 100% chance to decay into $\tilde{\chi}_1^0 \pi$, while in the higgsino-like case, the chargino branching fraction is set to 95.5% for $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_{1,2}^0 \pi^\pm$, 3% for $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_{1,2}^0 e \bar{\nu}_e$, and 1.5% for $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_{1,2}^0 \mu \bar{\nu}_\mu$ following the calculations in Ref. [150], where $\tilde{\chi}_1^0$ and $\tilde{\chi}_2^0$ are degenerate in mass.

For each mass point, the value of $x_{Q\text{cut}}$ is varied from 30 to 100 GeV in steps of 10 GeV and from 100 to 1000 GeV in steps of 100 GeV to test smaller and higher scales, while q_{cut} is set as the default value of $\max(x_{Q\text{cut}} + 10 \text{ GeV}, 1.5 \times x_{Q\text{cut}})$. In CMSSW, the generation of events with MadGraph5 is performed via gridpacks, which are compressed files that contain all of the information MG5 needs to simulate the processes. In summary, three cards contain the main information needed for the simulation of the AMSB processes: the param_card, which contains information about the model that has to be used in the simulation and what are

Table 4.1: SUSY parameters used to generate simulated signal samples for each considered chargino mass. The large mass scale of the squarks is denoted by the mass of the down squark $m_{\tilde{d}}$. The other parameters are described in the text. The parameters for $m_{\tilde{\chi}_1^\pm} \geq 900$ GeV are the same because, for larger values of $m_{3/2}$, even in the mAMSB, the sleptons become tachyonic. For the higher chargino masses, $m_{\tilde{\chi}_1^\pm}$ and $m_{\tilde{\chi}_1^0}$ are modified to the respective values using the 900 GeV sample as a template.

m_0 [GeV]	$m_{3/2}$ [TeV]	$\tan \beta$	$\text{sign}(\mu)$	$m_{\tilde{\chi}_1^\pm}$ [GeV]	Δm [GeV]	$m(\tilde{d})$ [GeV]
1500	35.1	5	+1	100.0	0.189	1649
1500	68.9	5	+1	200.0	0.174	2019
1500	103.7	5	+1	300.0	0.172	2494
1500	139.0	5	+1	400.0	0.173	3018
1500	174.4	5	+1	500.0	0.173	3561
1500	210.3	5	+1	600.0	0.173	4121
1500	246.4	5	+1	700.0	0.173	4686
1500	282.9	5	+1	800.0	0.174	5261
1500	320.2	5	+1	900.0	0.174	5845
1500	320.2	5	+1	1000.0	0.174	5845
1500	320.2	5	+1	1100.0	0.174	5845
1500	320.2	5	+1	1200.0	0.174	5845

the processes to be generated; the `run_card`, where the center of mass energy, protons PDF sets, generator-level cuts, the value of $x_{Q_{\text{cut}}}$, and more, are defined; and the customization card, where all the parameters calculated by IsaJet are input into the MadGraph5 simulation. While testing the jet matching parameters, the implementation of Pythia, which is included inside the MadGraph5 software, was used. However, in CMSSW, there is a hadronizer configuration file to set the parameters that Pythia will use for the hadronization and jet matching. Examples of these cards and configurations are displayed in Appendix B.

Figure 4.3 shows an example of the differential jet rate distribution for the chargino mass point of 700 GeV with a $x_{Q_{\text{cut}}} = 50$ GeV, where the distribution is smooth, as expected. Table 4.2 shows the parameters determined for each range of chargino masses.

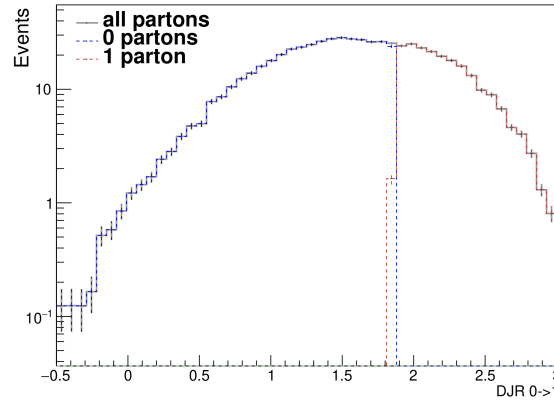


Figure 4.3: Differential jet rate distribution for the simulation of a 700 GeV chargino with $x_{Q_{\text{cut}}} = 50$ GeV and $q_{\text{cut}} = 75$ GeV. The blue and red distributions represent the processes with 0 and 1 extra parton, respectively.

Table 4.2: Values of $x_{Q_{\text{cut}}}$ and q_{cut} used for each range of chargino masses.

Chargino mass [GeV]	$x_{Q_{\text{cut}}}$ [GeV]	q_{cut} [GeV]
100–400	40.0	60.0
500–900	50.0	75.0
1000–1200	60.0	90.0

After the estimation of the jet merging parameters, the first sanity check that

was performed was the comparison of the events simulated by MadGraph5 + Pythia, with events simulated by Pythia-only (in the same way that was used in the previous disappearing tracks searches), for a subset of the mass points mentioned above, and a $c\tau$ of 100 cm. This check was important to make sure that the MG5-generated events were being affected by the jet-matching scheme. A relevant difference was already expected at the generator level, especially in variables that are related to the recoil of the charginos with the extra jets. Examples of such variables are the p_T of the leading jet, the p_T^{miss} and the p_T of the sum of the four-momentum of both produced electroweakinos, denoted as $p_T(\tilde{\chi}_1^\pm \tilde{\chi}_1^\mp / \tilde{\chi}_1^\pm \tilde{\chi}_1^0)$. As one example, Figure 4.4 shows the comparison of some variables of interest for a wino-like chargino of mass 700 GeV and 100 cm of $c\tau$, where 1 million events were generated with MG5 + PY8 or PY8-only. From top to bottom, left to right, the variables being compared are: the generated chargino p_T , η and ϕ , the generated pion p_T , the generated chargino $c\tau$ and decay length, the p_T of the highest p_T jet, the generated p_T^{miss} and $p_T(\tilde{\chi}_1^\pm \tilde{\chi}_1^\mp / \tilde{\chi}_1^\pm \tilde{\chi}_1^0)$, where the Pythia-only simulation sample is plotted in red and the MadGraph5 + Pythia simulation is plotted in blue. The ratio plots of MG5/PY8 show that the expected differences appear in the variables mentioned above, and in the expected region of larger jet p_T , i.e., the harder jets that a PS generator cannot accurately simulate.

The second check was related to the selections applied over the events to search for the disappearing tracks. A detailed description of the events' selection is given in Section 6.2, but, for this verification, it can be summarized into five sets of requirements, targeting distinct aspects:

- Triggering: the first stage of the selection requires that the events pass a selection of HLT paths related to the p_T^{miss} of the event;
- Basic selection: requires that the event has a high p_T^{miss} recoiling against a high p_T jet;
- Isolated tracks selection: selects a track with high p_T that is continuous, i.e., has no missing hits in the middle of the track, and is isolated from other reconstructed charged tracks;
- Candidate tracks selection: the selected tracks have to be separated from any charged SM lepton;
- Disappearing tracks selection: uses the two variables mentioned at the beginning of this chapter, E_{calo} and $N_{\text{miss}}^{\text{outer hits}}$, to very effectively discriminate SM particles from a BSM disappearing track.

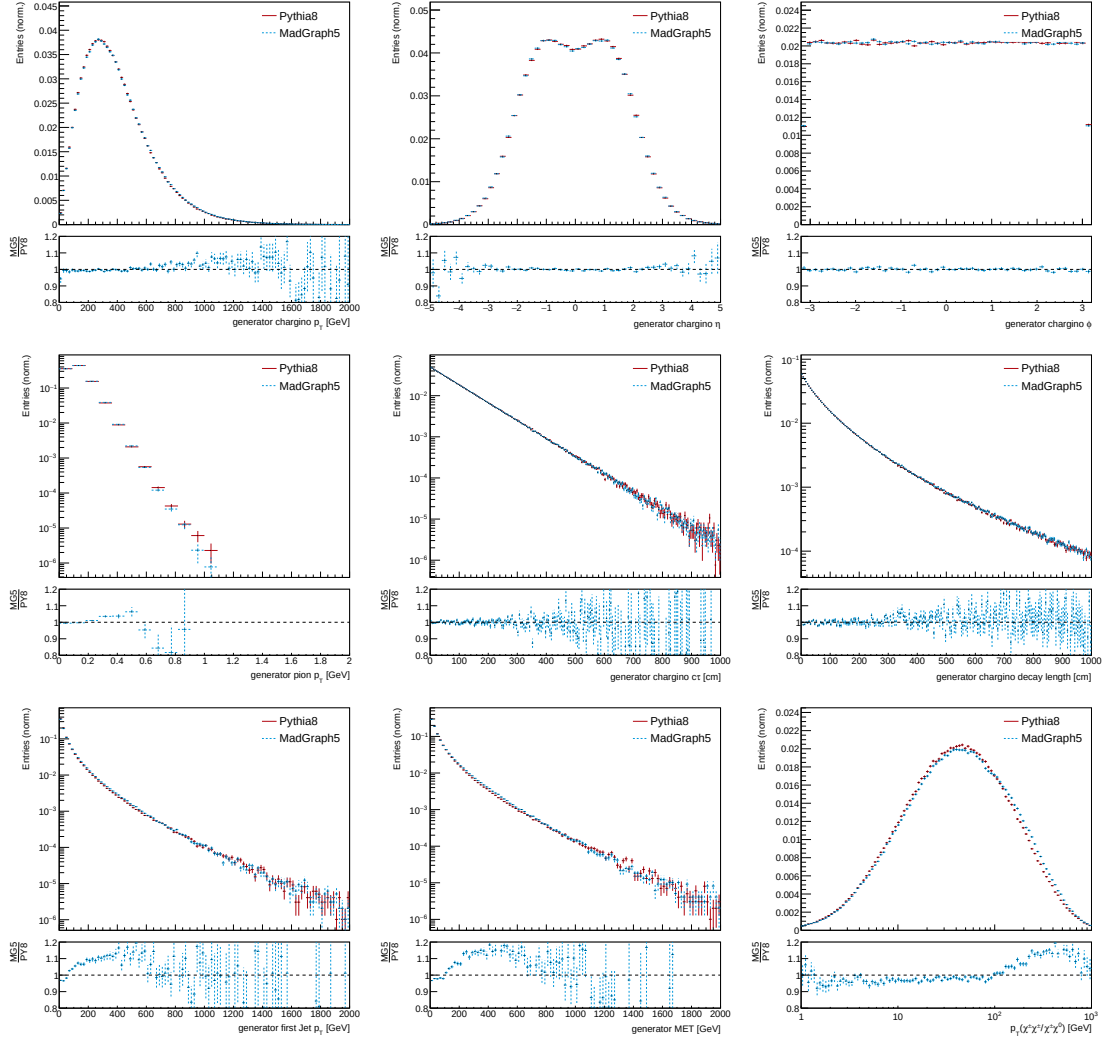


Figure 4.4: Comparison of some variables of the chargino of the AMSB process simulated with Pythia, which does not support the addition of extra hard partons (full red line), and MadGraph5 + Pythia with the addition of one extra hard parton and performing the jet matching algorithm (dashed blue line). As expected, the difference between both methods is clear in the jet p_T , generated p_T^{miss} , and the p_T of the summed four-momenta of the produced electroweakinos shown in the three bottom plots.

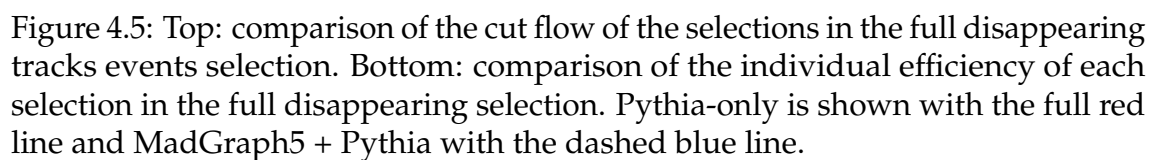
This check used each of the selections applied to the search for a disappearing track in what is called the cut flow. It displays the efficiency of each requirement, i.e., the ratio between the number of events that pass the selection with the number of events before the selection, when those are applied sequentially. These selections are applied over fully reconstructed events, where the software Geant4 10.7.2 [165–167] was used to simulate the interaction of particles with the detector material, and the reconstruction of physics objects was performed by CMSSW 13.0.13. Given the large amount of time needed for simulation and reconstruction, a single simulated data set of 50,000 events for a wino-like chargino of mass 700 GeV and lifetime of 100 cm/c was produced. The top plot of Figure 4.5 shows the cut flow for the events generated with Pythia-only (red) and MadGraph5 + Pythia (blue), where it is possible to notice a difference in the efficiencies after the cuts. The bottom plot shows the individual efficiency of each of the selection requirements, where the differences that arise from the MadGraph5 + Pythia simulation are related to the triggering, the p_T^{miss} and the jet p_T selections, as expected.

Finally, the last check was on some interesting variables of reconstructed objects. Figure 4.6 shows the comparison between PY8-only (red, full line) and MG5 + PY8 (blue, dashed line) reconstructed events, with the same samples used for the cut flow check above. From left to right, top to bottom, the variables plotted are: the track p_T , η , ϕ , number of missing inner, middle, outer, and valid hits, and the PF p_T^{miss} .

In addition to exploring a variety of chargino masses, this analysis also considers multiple chargino lifetimes as reference benchmarks. While the AMSB framework states that the lifetime of a chargino is determined by the mass difference between the chargino and neutralino, treating the lifetime as an adjustable parameter enables the analysis for a wider spectrum of models. By using a limited number of lifetime values, intermediate scenarios can be studied through lifetime reweighting. To modify a sample originally generated with a mean lifetime τ_{src} to a desired mean lifetime τ_{dst} , the following reweighting factor is applied:

$$w_\tau = \prod_i \frac{\left(\frac{1}{\tau_{\text{dst}}} e^{-\tau_i/\tau_{\text{dst}}} \right)}{\left(\frac{1}{\tau_{\text{src}}} e^{-\tau_i/\tau_{\text{src}}} \right)}, \quad (4.4)$$

where τ_i denotes the actual lifetime of the i -th chargino in the event ($i = 1, 2$ for a



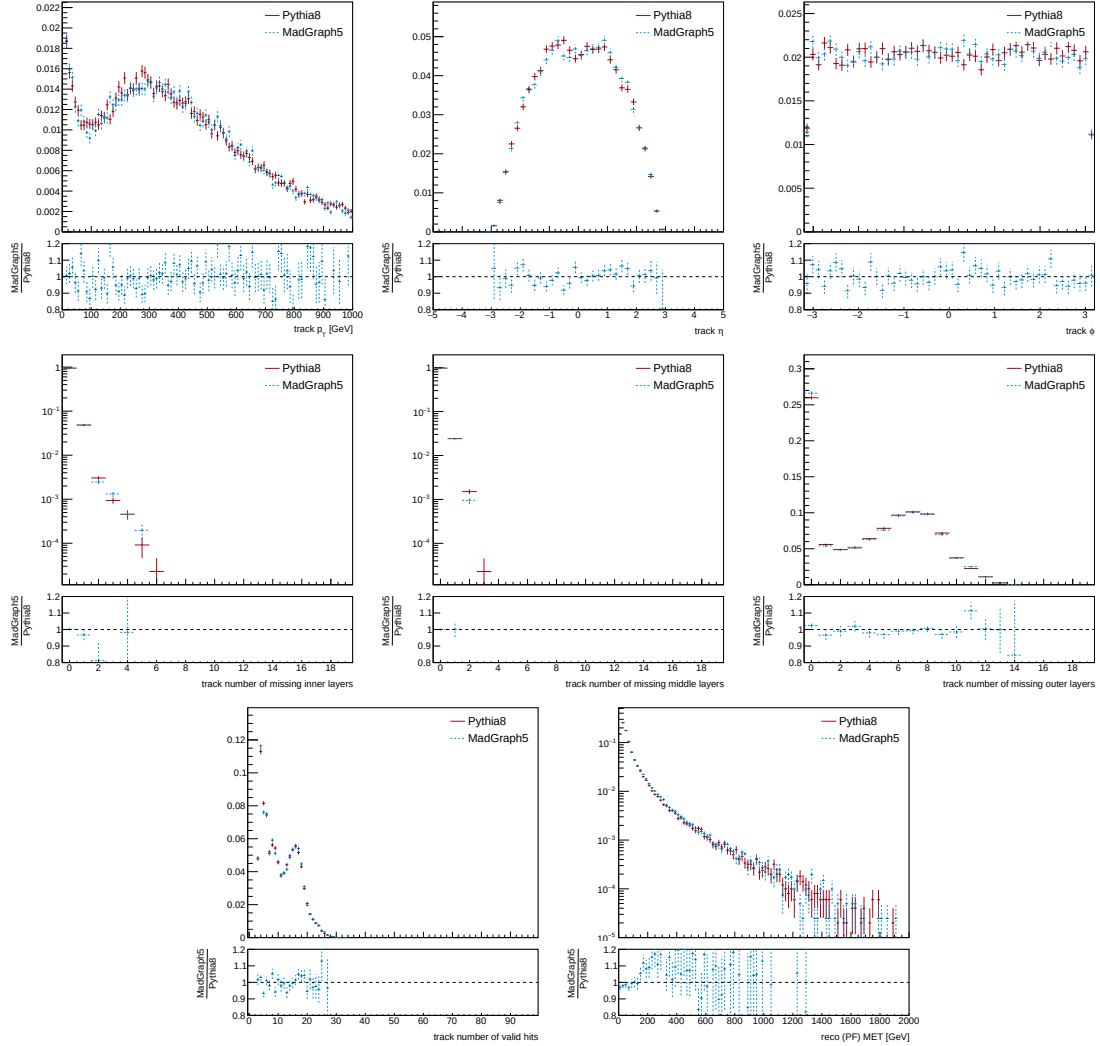


Figure 4.6: Comparison of some variables of reconstructed objects of the AMSB process simulated with Pythia, which does not support the addition of extra hard partons (full red line), and MadGraph5 + Pythia with the addition of one extra hard parton and performing the jet matching algorithm (dashed blue line). The difference between the methods is less clear in this case, due to the large statistical fluctuations.

$pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp$ process and $i = 1$ for a $pp \rightarrow \tilde{\chi}_{1,2}^0 \tilde{\chi}_1^\pm$ process). This weight is computed for each event individually, with the condition that $\tau_{\text{dst}} < \tau_{\text{src}}$ to ensure that events in the tail of the original lifetime distribution are not weighed up. This reweighting transforms the distribution with mean τ_{src} into one resembling a lifetime of τ_{dst} , as shown in Figure 4.7. Table 4.3 summarizes the target lifetime values and their respective source samples.

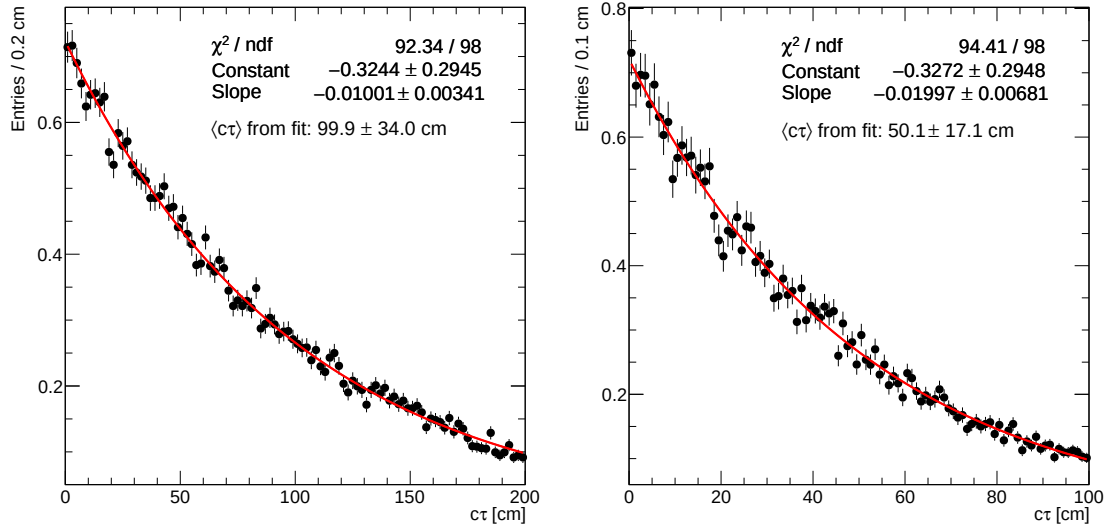


Figure 4.7: Generator-level distributions of actual chargino lifetimes. Both plots come from a sample with a generated mean lifetime of 100 cm/c. The left panel shows the original distribution, while the right panel displays the reweighting done to a target mean lifetime of 50 cm/c. In each case, the red curve represents an exponential fit to the distribution.

Table 4.3: Summary of target chargino lifetimes achieved through reweighting, along with the original sample lifetimes.

original lifetime [cm/c]	target lifetimes [cm/c]
10	0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
100	20, 30, 40, 50, 60, 70, 80, 90, 100
1,000	200, 300, 400, 500, 600, 700, 800, 900, 1,000
10,000	2,000, 3,000, 4,000, 5,000, 6,000, 7,000, 8,000, 9,000, 10,000

Since the production of electroweakino pairs is simulated at leading order with the addition of at most one hard parton, the cross section of the simulated processes is reweighted based on more precise estimations. Tables 4.4 for the wino-like case

and 4.5 for the higgsino-like case display the cross section values calculated at approximate next-to-next-to leading order (aNNLO) plus next-to-next-to leading logarithmic (NNLL) precision with Resummino [168, 169], using the MSTW2008 [170] PDF sets. The final cross sections and uncertainties are calculated using the PDF4LHC recommendations for the two sets of cross sections [171].

Table 4.4: Cross sections for electroweak production of wino-like charginos calculated at aNNLO+NNLL with center-of-mass energy of $\sqrt{s} = 13.6$ TeV. The cross sections for $pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp$ and $pp \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm$ are listed separately, along with the total cross section, which is the sum of these two contributions.

$m(\tilde{\chi}_1^\pm)$ [GeV]	$\sigma(pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp)$ [pb]	$\sigma(pp \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm)$ [pb]	total σ [pb]
100	$12.84^{+0.44}_{-0.51}$	$24.92^{+0.64}_{-0.74}$	$37.76^{+0.78}_{-0.90}$
200	$1.012^{+0.035}_{-0.035}$	$2.016^{+0.058}_{-0.059}$	$3.028^{+0.068}_{-0.069}$
300	$0.2155^{+0.0087}_{-0.0088}$	$0.437^{+0.015}_{-0.015}$	$0.652^{+0.018}_{-0.018}$
400	$0.0667^{+0.0032}_{-0.0032}$	$0.1378^{+0.0058}_{-0.0058}$	$0.2048^{+0.0067}_{-0.0067}$
500	$0.0255^{+0.0014}_{-0.0014}$	$0.0532^{+0.0026}_{-0.0026}$	$0.0787^{+0.0030}_{-0.0030}$
600	$0.0110^{+0.00073}_{-0.00073}$	$0.0233^{+0.0013}_{-0.0013}$	$0.0343^{+0.0015}_{-0.0015}$
700	$0.00519^{+0.00040}_{-0.00040}$	$0.01111^{+0.00074}_{-0.00074}$	$0.01629^{+0.00084}_{-0.00084}$
800	$0.00260^{+0.00023}_{-0.00023}$	$0.00562^{+0.00044}_{-0.00044}$	$0.00822^{+0.00050}_{-0.00050}$
900	$0.00137^{+0.00015}_{-0.00015}$	$0.00298^{+0.00027}_{-0.00027}$	$0.00435^{+0.00031}_{-0.00031}$
1000	$0.000745^{+0.000095}_{-0.000095}$	$0.00163^{+0.00018}_{-0.00018}$	$0.00238^{+0.00020}_{-0.00020}$
1100	$0.000418^{+0.000064}_{-0.000064}$	$0.00092^{+0.00012}_{-0.00012}$	$0.00134^{+0.00014}_{-0.00014}$
1200	$0.000241^{+0.000045}_{-0.000045}$	$0.000531^{+0.000084}_{-0.000084}$	$0.000771^{+0.000096}_{-0.000096}$

4.2 Using MiniAOD Samples for Run 3 Data Analysis

In the Run 2 analysis, the estimation of the energy deposited in the calorimeters associated with a given track was calculated using the energy of the reconstructed hits (RecHits) in the calorimeters. The energy of all ECAL and HCAL RecHits in a cone of $\Delta R = 0.5$ around a given track was summed, and, from the final value, a contribution related to PU was subtracted. This method of calculating E_{calo} ensures that any amount of energy measured by the calorimeters around the track will be considered in this variable. The downside of this method is that the full calorimeter RecHits information is only available in the format of raw detector measurements (which is impractical for data analysis), or in a data format named Analysis Data Object (AOD). Two main issues arise when using files of type AOD for data analysis: these files are not readily available for usage, given that they are

Table 4.5: Cross sections for electroweak production of higgsino-like charginos calculated at aNNLO+NNLL with center-of-mass energy of $\sqrt{s} = 13.6$ TeV. The $\tilde{\chi}_2^0$ is completely mass degenerate with the $\tilde{\chi}_1^0$ with the same production cross sections, so the total includes an additional contribution equal to that listed for $\sigma(\text{pp} \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm)$.

$m(\tilde{\chi}_1^\pm)$ [GeV]	$\sigma(\text{pp} \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp)$ [pb]	$\sigma(\text{pp} \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm)$ [pb]	total σ [pb]
100	$3.329^{+0.110}_{-0.130}$	$6.229^{+0.161}_{-0.185}$	$15.79^{+0.25}_{-0.29}$
200	$0.2823^{+0.0096}_{-0.0098}$	$0.5040^{+0.0145}_{-0.0147}$	$1.2903^{+0.0226}_{-0.0230}$
300	$0.0612^{+0.0025}_{-0.0025}$	$0.1092^{+0.0038}_{-0.0038}$	$0.2796^{+0.0060}_{-0.0060}$
400	$0.0192^{+0.0009}_{-0.0009}$	$0.0345^{+0.0015}_{-0.0015}$	$0.0882^{+0.0023}_{-0.0023}$
500	$0.00735^{+0.00041}_{-0.00041}$	$0.01331^{+0.00066}_{-0.00066}$	$0.03397^{+0.00102}_{-0.00102}$
600	$0.00319^{+0.00021}_{-0.00021}$	$0.00583^{+0.00034}_{-0.00034}$	$0.01485^{+0.00052}_{-0.00052}$
700	$0.00151^{+0.00012}_{-0.00012}$	$0.00278^{+0.00019}_{-0.00019}$	$0.00707^{+0.00029}_{-0.00029}$
800	$0.000760^{+0.000069}_{-0.000069}$	$0.001407^{+0.000110}_{-0.000110}$	$0.003574^{+0.000170}_{-0.000170}$
900	$0.000401^{+0.000043}_{-0.000043}$	$0.000745^{+0.000068}_{-0.000068}$	$0.001891^{+0.000106}_{-0.000106}$
1000	$0.000219^{+0.000029}_{-0.000029}$	$0.000409^{+0.000044}_{-0.000044}$	$0.001037^{+0.000069}_{-0.000069}$

stored in physical tapes, and a request to replicate the data to some disk is needed; the average size of each event inside an AOD file is on the order of 0.4 megabytes, which implies in a high time for processing and analyzing each AOD sample [172]. In cases where this has to be done for billions of events, it becomes unfeasible.

In this search, another variable is being tested to check if it is suitable to correctly select disappearing track events. It is based on the ECAL and HCAL energy from the nearest calorimeter jet (CaloJet) to a given track. A calorimeter jet is an object reconstructed with information only from the calorimeter RecHits. Even though it does not consider every RecHit around a track, it serves as a proxy to the E_{calo} estimation mentioned above, and it is available in the MiniAOD data format, which is a reduced version of the AOD. This data format is promptly available for analysts to use, and, given the reduced size and amount of information, where the event size is around 50 kilobytes [172], it is faster to process each event $\mathcal{O}$ (10–100 ms).

The distributions of both variables are shown in Figure 4.8. It is possible to see a clear difference between the RecHit E_{calo} (blue, full line) and the CaloJet E_{calo} (red, dashed line). To check the impact of this modification on the selection of disappearing track events, signal samples of wino-like charginos for the mass

points of 100, 400, 700, and 1200 GeV and lifetimes of 10, 100, 1000, and 10000 cm/c were used. Table 4.6 shows the number of events that pass the full disappearing tracks selection using each E_{calo} , and the percentage of extra events in the case with RecHit E_{calo} . Although there is a large difference in the way E_{calo} is calculated, the discrepancy between the selection using each method is small.

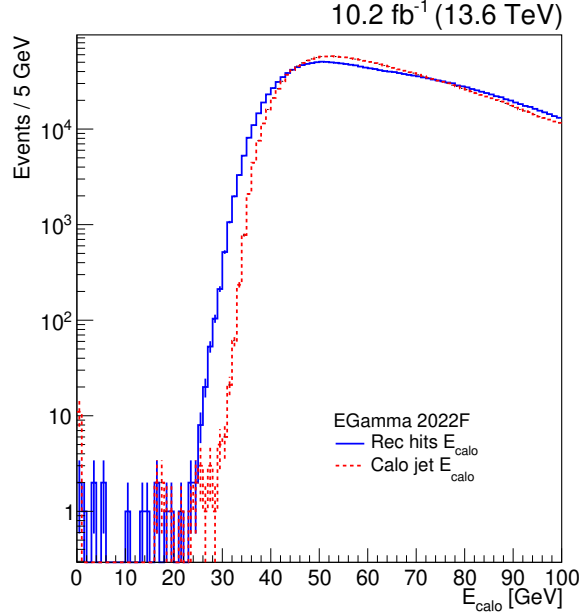


Figure 4.8: Comparison of RecHit (blue) and CaloJet E_{calo} (red) distributions calculated from 10.2 fb^{-1} 2022 data, where the events contain electrons and photons.

4.2.1 Datasets used for the Analysis

In this search, all of the datasets processed, either from collected data, SM MC, or signal MC, are in the MiniAOD data format. This is only possible by using the CaloJet E_{calo} variable. The used samples comprise 62.5 fb^{-1} of collected data in 2022 and 2023 at $\sqrt{s} = 13.6 \text{ TeV}$. Several datasets are used: JetMET datasets, used for the signal region of the search; EGamma and Muon datasets², used for background and systematic uncertainties estimation; signal MC samples generated with the masses and lifetimes displayed in Section 4.1; and SM MC samples of $Z \rightarrow ll$, single top, $t\bar{t}$, WW, WZ, ZZ, $W \rightarrow l\nu$, $Z \rightarrow \nu\bar{\nu}$ and QCD processes. $Z \rightarrow ll$, $W \rightarrow l\nu$, and $Z \rightarrow \nu\bar{\nu}$ samples are produced at LO with MadGraph5 and

²The datasets are defined using the trigger paths used to collect a given event. Events collected using $p_{\text{T}}^{\text{miss}}$ and/or jet triggers are saved in the JetMET dataset; events collected with single or double lepton triggers (or triple, in some cases) are saved in the respective lepton dataset.

Table 4.6: Number of events after the disappearing tracks selection when using RecHit E_{calo} and CaloJet E_{calo} , and the relative difference in percentage of the number of events obtained with each method.

	$\frac{\# \text{ ev. Rec hit } E_{\text{calo}}}{\# \text{ ev. CaloJet } E_{\text{calo}}} / \% \text{ of extra events in RecHit } E_{\text{calo}}$			
	100 GeV	400 GeV	700 GeV	1200 GeV
10 cm	$\frac{121}{122} / -0.82\%$	$\frac{239}{234} / 2.1\%$	$\frac{258}{252} / 2.4\%$	$\frac{270}{263} / 2.7\%$
100 cm	$\frac{136}{135} / 0.74\%$	$\frac{841}{828} / 1.6\%$	$\frac{1289}{1269} / 1.6\%$	$\frac{1649}{1641} / 0.49\%$
1000 cm	$\frac{26}{25} / 4.0\%$	$\frac{212}{205} / 3.4\%$	$\frac{385}{382} / 0.79\%$	$\frac{671}{664} / 1.1\%$
10000 cm	$\frac{20}{20} / 0.0\%$	$\frac{155}{153} / 1.3\%$	$\frac{392}{389} / 0.77\%$	$\frac{700}{698} / 0.29\%$

Pythia with the addition of up to 4 extra hard partons, where the jet matching is performed with the MLM algorithm. WW, WZ, ZZ, and QCD processes are generated at LO with Pythia. The single top processes $pp \rightarrow tq$ and $pp \rightarrow tW$, and the $t\bar{t}$ samples are produced at LO with Powheg [173–177] and Pythia. Finally, the single top $pp \rightarrow tb$ samples are generated at NLO with MadGraph and Pythia. The collected data for 2022 are divided into 5 eras: C, D, E, F, and G, where an era is related to the conditions of the detector and the reconstruction algorithm in a given period. The 2023 collected data is divided into 2 eras: C and D. Due to a couple of issues during data taking, described in more detail in Section 6.2, the data-taking periods will also be split as 2022 (combining 2022C and D), 2022EE (combining 2022E, F, and G), 2023 (for 2022C) and 2023BPix (for 2022D).

4.3 Issues with Triggering

The signature of a disappearing track is relatively hard to trigger at the L1T, given that tracks are not reconstructed at this stage. To work around this difficulty, $p_{\text{T}}^{\text{miss}}$ based algorithms are used. At the HLT, which performs an event reconstruction closer to what is performed offline³, even though it has a timing limitation, it can reconstruct every physical object in an event. More specifically, the HLT employs the so-called particle flow (PF) algorithms [178] in the reconstruction of events, which use a combination of the information from multiple subdetectors to

³In this context, offline means that the events are reconstructed almost without limitations of time and resources.

reconstruct and calibrate the properties of physical objects.

The elements for the PF reconstruction are: tracks, which can be from the tracker or the muon system, and calorimeter clusters. The so-called link algorithm is then used to link the information from the subsystems to create PF blocks, which are single particles or collections of particles. The distinct PF elements are linked based on their proximity in the (η, ϕ) plane. Each PF block then goes through the reconstruction of the given final state object: muons and electrons (including bremsstrahlung photons) are identified first, followed by isolated photons, and then hadrons (charged and neutral). Misreconstructed tracks are filtered out to improve accuracy. Every identified physics object gets removed from the PF blocks to ease the remaining steps of the algorithm. After all particles are reconstructed, a post-processing step finalizes the event reconstruction. Muons are reconstructed using information from the tracker, the calorimeters (since their energy deposit in the ECAL/HCAL should be small), and the muon chambers. Electrons are identified using information from the tracker and the calorimeters. Isolated photons are reconstructed together with electrons, using ECAL information, provided that the ECAL clusters are not linked to any track. The remaining tracks and calorimeter clusters are used to identify charged hadrons, neutral hadrons, nonisolated photons (e.g., from π^0 decays), and additional muons from the decay of charged hadrons. From the PF objects, it is possible to define two types of p_T^{miss} : the calo p_T^{miss} , which is the amount of missing transverse momentum calculated from all the energy deposits in the calorimeters; and the PF p_T^{miss} , which is calculated from all the PF objects mentioned above.

The AMSB model can generate p_T^{miss} in one of three ways:

- A $\tilde{\chi}_1^\pm$ can be produced with a $\tilde{\chi}_1^0$, where the $\tilde{\chi}_1^\pm$ reaches the muon chambers (displayed in Figure 4.9, top);
- Two $\tilde{\chi}_1^\pm$ can be produced and only one reaches the muon chambers (shown in Figure 4.9, bottom);
- The electroweakino pair can be accompanied by ISR (displayed in Figure 4.10).

In the first two cases, the $\tilde{\chi}_1^\pm$ that reaches the muon chambers is reconstructed as a muon, and therefore contributes visible momentum to the p_T^{miss} estimated by the PF reconstruction, but not to calorimeter-based p_T^{miss} . On the other hand, the $\tilde{\chi}_1^0$

contributes no visible momentum since it interacts only weakly. The $\tilde{\chi}_1^\pm$ that fails to reach the muon chambers also contributes no visible momentum because, being a track with no calorimeter energy nor muon chamber hits, it is considered a fake track by particle flow and ignored. Finally, in the third case, if the ISR has sufficient p_T , then it can contribute substantially to both PF p_T^{miss} and to calorimeter-based p_T^{miss} .

Again, as there is no tracking available at L1, the only type of p_T^{miss} that can be used at L1 is calorimeter-based p_T^{miss} . As such, a signal event with p_T^{miss} generated by a high- p_T ISR jet is precisely the category targeted in this search, hence the importance of a more accurate simulation of events with extra hard partons.

4.3.1 Triggers used in the search

This search uses data collected with the logical OR of several p_T^{miss} triggers. Various single-lepton triggers are also used for the estimation of backgrounds and studies of systematic uncertainties. The complete list of triggers used is shown in Table 4.7. Due to the lack of a dedicated single tau trigger in the tau sample, the last path of the table was used to study a tau control region.

Some issues affecting these paths arose throughout the 2022 and 2023 data-taking periods. In the middle of era C of 2022, an issue with the jet scale calibrations at the Level-1 trigger caused a decrease in efficiency of several inclusive p_T^{miss} paths. This is treated as an extra systematic uncertainty added to the search, included in Section 6.5. Finally, in era D of 2023, an issue with the pixel barrel caused a decrease in the efficiency of track reconstruction. However, due to the addition of a recovery module on the HLT tracks reconstruction, the effect on the efficiency of the used paths is found to be negligible.

The `HLT_MET105_IsoTrk50_v*` path was developed specifically for the disappearing tracks search, was deployed and monitored throughout the Run 2 data-taking, and is still used for the Run 3 data analysis. The p_T^{miss} threshold was kept the same concerning the Run 2 algorithm. For Run 3, there was also the deployment and monitoring of path `HLT_PFMET105_IsoTrk50_v*`, which makes use of a lower threshold PF p_T^{miss} filter to increase the rates of relevant events to the analysis. The paths consist of three/four steps depending on the

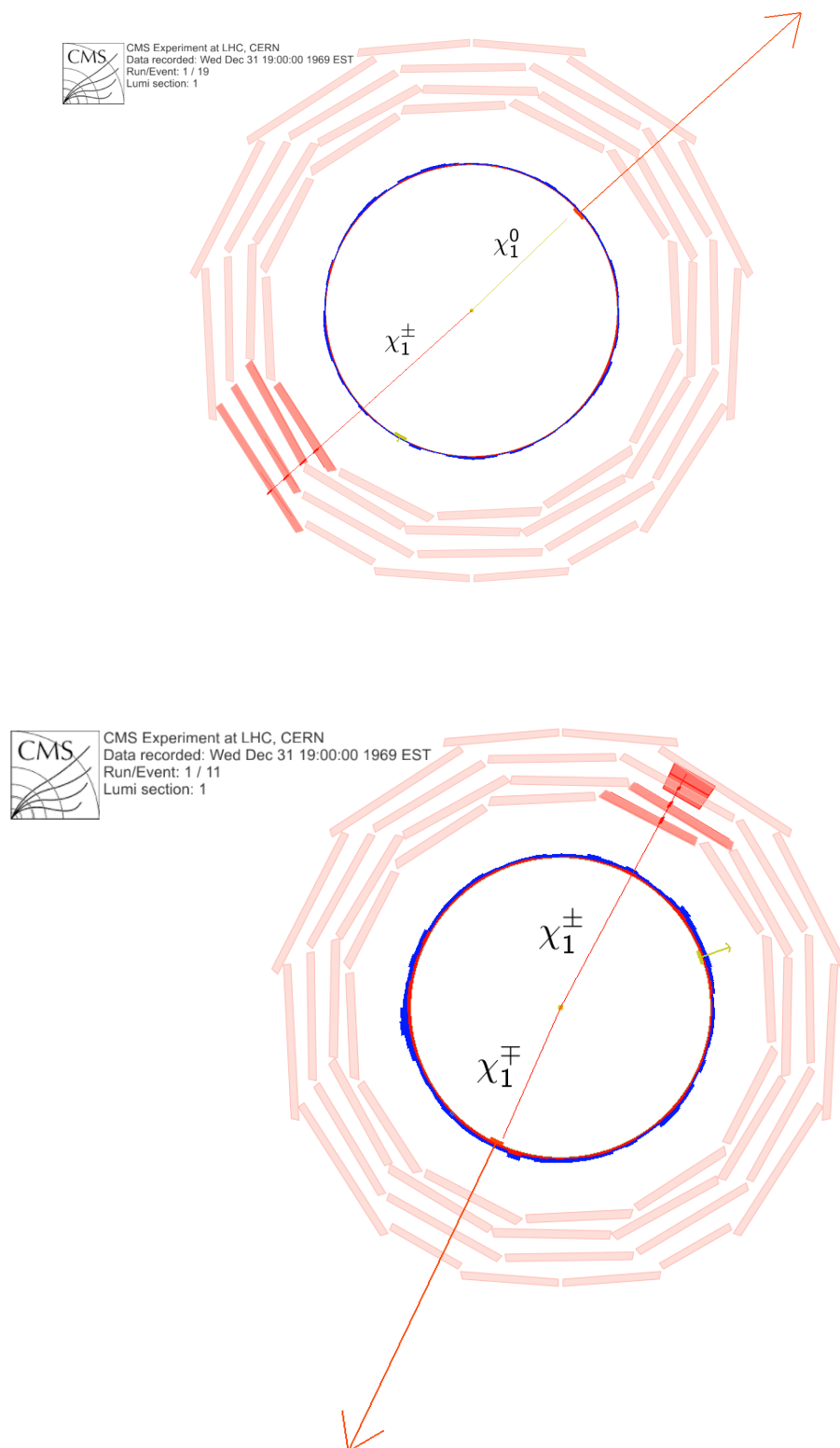


Figure 4.9: Event displays of simulated signal events, one of $pp \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm$ (top) and one of $pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp$ (bottom). The PF $\vec{p}_T^{\text{miss}}$ vector is shown as a red arrow and the calorimeter-based $\vec{p}_T^{\text{miss}}$ vector is shown as a gold arrow.

Table 4.7: Triggers used in the search. The MET data set is used as the search data set and for the evaluation of fake track background systematic uncertainties, and the single-lepton data sets are used for background estimation and systematic uncertainty evaluation. Path `HLT_IsoMu20_eta2p1_LooseDeepTauPFTauHPS27_eta2p1_CrossL1_v*` is used to select events enriched in low p_T tau leptons.

Primary Data Set	Trigger Path
MET	<code>HLT_MET105_IsoTrk50_v*</code>
	<code>HLT_MET120_IsoTrk50_v*</code>
	<code>HLT_PFMET105_IsoTrk50_v*</code>
	<code>HLT_PFMET120_PFMHT120_IDTight_v*</code>
	<code>HLT_PFMET130_PFMHT130_IDTight_v*</code>
	<code>HLT_PFMET140_PFMHT140_IDTight_v*</code>
	<code>HLT_PFMETNoMu120_PFMHTNoMu120_IDTight_v*</code>
	<code>HLT_PFMETNoMu130_PFMHTNoMu130_IDTight_v*</code>
	<code>HLT_PFMETNoMu140_PFMHTNoMu140_IDTight_v*</code>
	<code>HLT_PFMETNoMu120_PFMHTNoMu120_IDTight_PFHT60_v*</code>
	<code>HLT_PFMETNoMu110_PFMHTNoMu110_IDTight_FilterHF_v*</code>
	<code>HLT_PFMETNoMu120_PFMHTNoMu120_IDTight_FilterHF_v*</code>
	<code>HLT_PFMETNoMu130_PFMHTNoMu130_IDTight_FilterHF_v*</code>
	<code>HLT_PFMETNoMu140_PFMHTNoMu140_IDTight_FilterHF_v*</code>
	<code>HLT_PFMET120_PFMHT120_IDTight_PFHT60_v*</code>
EGamma	<code>HLT_Ele32_WPTight_Gsf_v*</code>
Muon	<code>HLT_IsoMu24_v*</code>
	<code>HLT_IsoMu20_eta2p1_LooseDeepTauPFTauHPS27_eta2p1_CrossL1_v*</code>

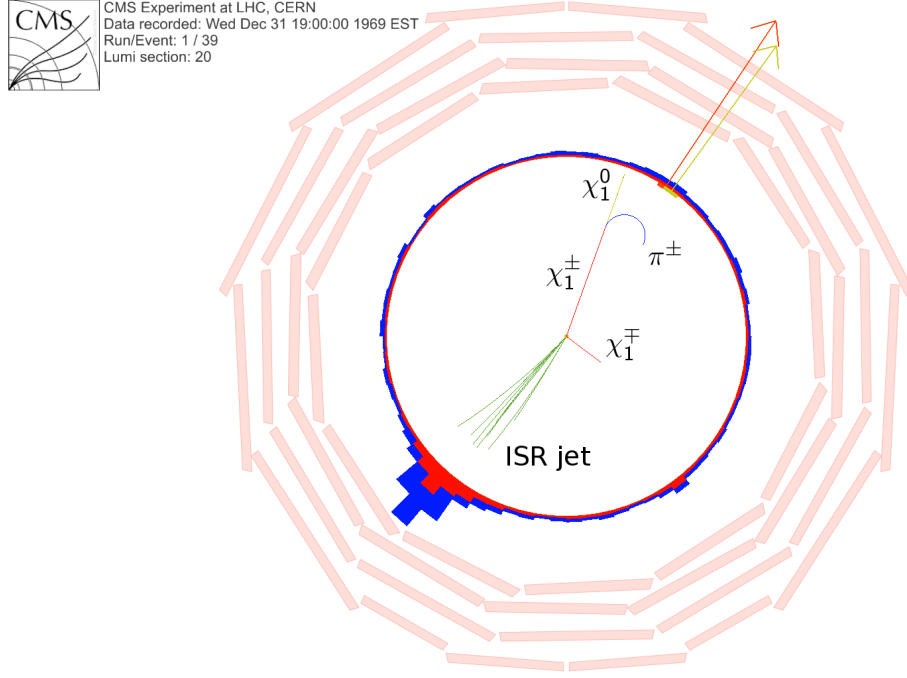


Figure 4.10: Event display of a simulated $pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp$ event with an ISR gluon jet. The PF $\vec{p}_T^{\text{miss}}$ vector is shown as a red arrow and the calorimeter-based $\vec{p}_T^{\text{miss}}$ vector is shown as a gold arrow.

type of p_T^{miss} :

1. logical OR of several L1 p_T^{miss} algorithms
2. calo p_T^{miss} filter, `hltMET105` (or `hltMET75` in the PFMET path)
3. track filter, `hltTrk50Filter`
4. PF p_T^{miss} filter, `hltPFMET105` (only in the PFMET path)

At HLT the p_T^{miss} filter requires calo $p_T^{\text{miss}} > 105$ GeV, and the PF p_T^{miss} filter requires PF $p_T^{\text{miss}} > 105$ GeV. The track filter is processed only for events passing the p_T^{miss} filter and requires at least one HLT track to pass the following criteria:

- $p_T > 50$ GeV;
- track-based isolation $< 0.05 p_T$;
- ≥ 5 hits in the tracker;
- no missing inner hits;
- no missing middle hits

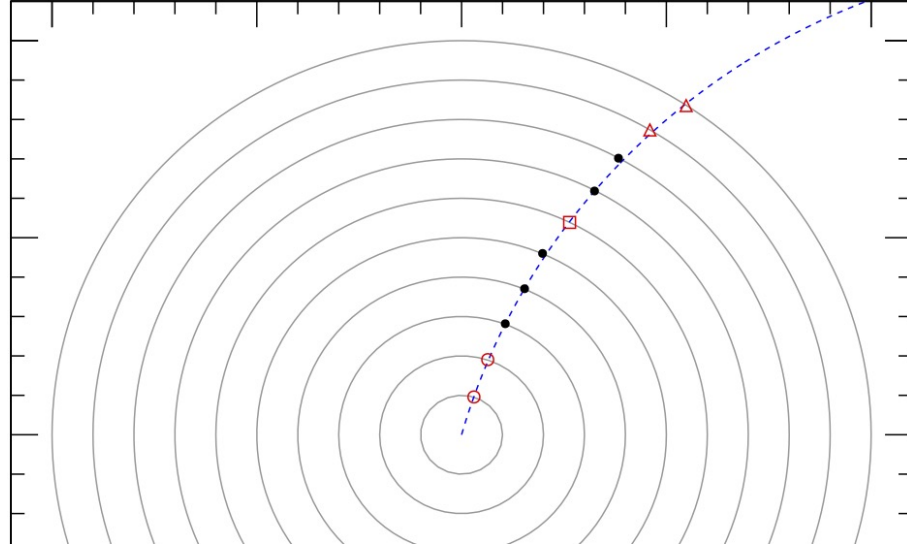


Figure 4.11: Cartoon of a track with measured hits (black points), missing inner hits (red open circles), missing middle hits (red open squares), and missing outer hits (red open triangles). This track would not pass the `HLT_MET105_IsoTrk50_v*` path selection, since it has two missing inner hits and one missing middle hit.

where missing inner hits are defined as how many hits should be there from the trajectory crossing with active layers, but are not there, counting them inwards from the first layer that has a hit, and missing middle hits are how many hits should be there in between the innermost and outermost hits associated to the track. Figure 4.11 shows a scheme of a track missing inner, middle, and outer (where missing outer hits refer to the variable mentioned at the beginning of Chapter 4). In other words, the hits on the HLT track are required to be consecutive, beginning in the innermost layer of the tracker through which the track traverses. The track-based isolation is calculated simply as the scalar sum of the p_T of all tracks reconstructed in the HLT down to $p_T = 50$ MeV within $\Delta R < 0.3$ of the track in question ⁴.

The calculation of efficiencies for the above triggers relies on the ratio of two quantities: the number of events after and before the path selection. In this case, the expression used is:

$$\text{Trigger efficiency} = \frac{\text{Number of events passing base selection AND trigger path}}{\text{Number of events passing base selection}}, \quad (4.5)$$

⁴No accounting for PU was present in the HLT track isolation calculation during 2022 and 2023.

where the base selection requires that the events have at least one high p_T isolated muon. These efficiencies are plotted as a function of $p_T^{\text{miss, no } \mu}$, which is p_T^{miss} calculated offline with the p_T of all reconstructed muons counted as invisible, as in Figure 4.12.

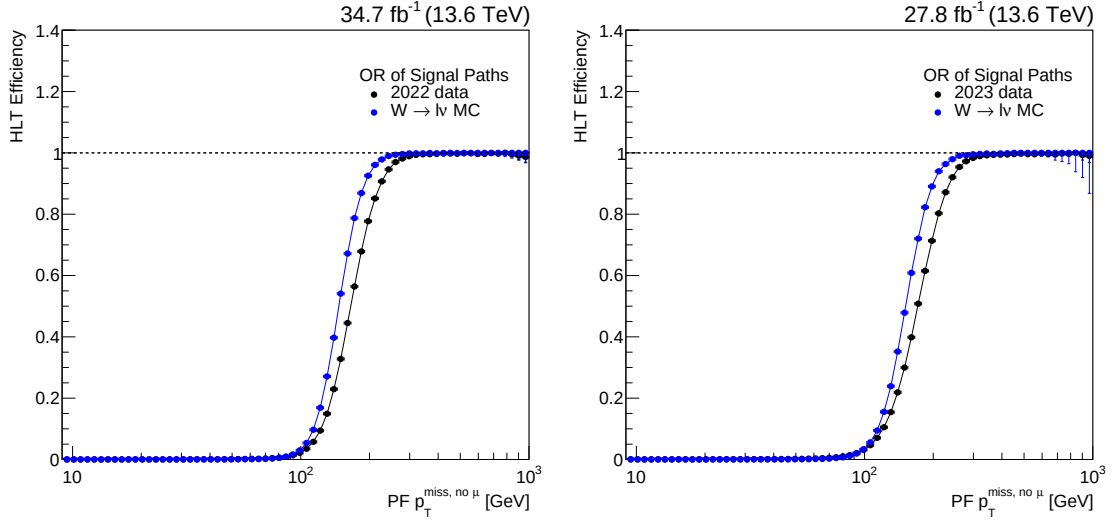


Figure 4.12: Efficiency of the combination of p_T^{miss} triggers used in the search for simulated $W \rightarrow l\nu$ and experimental data for 2022 (left) and 2023 (right) data and simulations. The efficiency is plotted only with respect to $p_T^{\text{miss, no } \mu}$, with the dependence on the track p_T integrated over, as described in Section 6.4.1.

Besides searching for disappearing tracks in CMS-collected data, this work also aimed at improving the data collection capability of the $p_T^{\text{miss}} + \text{IsoTrk}$ paths. Those paths have two main issues: the efficiency of the paths is limited by the efficiency of the tracking reconstruction at the HLT [179, 180]; and the rate at which those paths trigger on events is small, on the order of 5 Hz. The top plot of Figure 4.13 displays the efficiency of the `HLT_MET105_IsoTrk50` as a function of $p_T^{\text{miss, no } \mu}$, where it can be seen that it reaches a plateau around 70%. The bottom plots show that this plateau is caused solely by the track leg of the path, given that the efficiency of the $p_T^{\text{miss, no } \mu}$ filter (left) reaches 100%, while the IsoTrk leg efficiency (right) has a maximum of 70% efficiency when plotted as a function of the selected muon p_T . The IsoTrk leg efficiency is estimated as:

$$\text{Trigger efficiency} = \frac{\text{Events passing base selection AND hltMET105 AND trigger path}}{\text{Events passing base selection AND hltMET105}}. \quad (4.6)$$

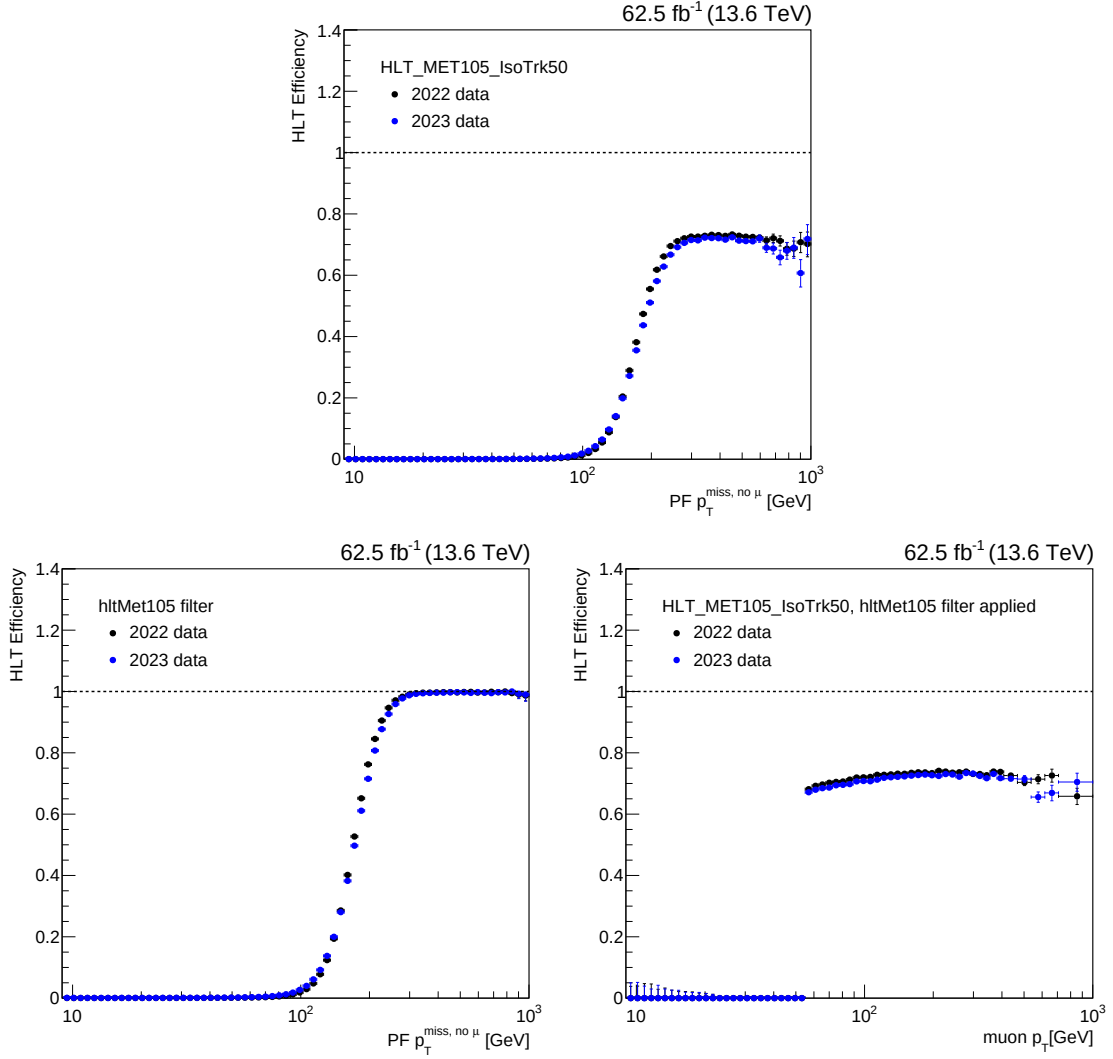


Figure 4.13: Efficiency of the HLT_MET105_IsoTrk50 and its filters calculated with experimental data for 2022 (black) and 2023 (blue) data. Top: HLT_MET105_IsoTrk50 efficiency plotted with respect to $p_T^{\text{miss, no } \mu}$. Bottom left: hltMET105 efficiency plotted with respect to $p_T^{\text{miss, no } \mu}$. Bottom right: hltTrk50Filter efficiency plotted with respect to muon p_T .

To improve the rate of the $p_T^{\text{miss}} + \text{IsoTrk}$ paths, two distinct ways are possible: increasing the efficiency of the path, and improving the overall rate of HLT, given that the small rate available for this path is also related to the limited resources

available to the collaboration. Working on the efficiency of the path would conflict with the limited available rate set by the collaboration. The increase in the HLT rate is motivated by the upgrade to the HL-LHC, where the collaboration has to be able to collect around five times more events than what is currently performed. This naturally increases the rate of $p_T^{\text{miss}} + \text{IsoTrk}$ paths. However, the large increase in the amount of events to be triggered on leads to the need for changes in the reconstruction algorithms.

Chapter 5

Improvement of the Pixel Tracks Reconstruction Algorithm

During Run 3, the instantaneous luminosity achieved by the LHC was around $2 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$, which implies approximately 60 concurrent pp collisions happening every bunch crossing. These collisions produce a few thousand particles that will traverse the CMS detector. Closer to the IP, the environment is densely populated by charged particles that must be reconstructed. In the next long shutdown (LS3)¹ the LHC will undergo a significant upgrade to increase its luminosity, known as the High-Luminosity LHC (HL-LHC) [97] project. This will increase the instantaneous luminosity of the accelerator by a factor of $\sim 2.5\text{--}3.5$ and, consequently, the average number of simultaneous interactions to $\sim 140\text{--}200$, implying in an even larger number of charged particles to be reconstructed. To exploit the higher luminosity, the CMS experiment will undergo various upgrades, collectively called the Phase-2 Upgrade, mentioned in Chapter 3, and the full detector readout rate will be increased from the current 100 kHz to 750 kHz [113]. Given the increase in event complexity, the HLT physics reconstruction will be significantly affected, and the HLT farm would be expected to require a processing power increase by two orders of magnitude, if no actions were taken [114].

Some of the objects that will be affected the most are the pixel tracks and vertices, i.e., the trajectory of the charged particles and their point of origin, reconstructed using only the information from the pixel tracker: the environment where these objects are located is very dense particle-wise, the detector granularity is very high, and the high PU will imply a harder combinatorial problem to be solved to attribute trajectories to individual particles. Also, the Phase-2 upgrade of the CMS pixel tracker [107] will increase the number of layers and channels, and consequently, its granularity, which will contribute to an increase in timing in

¹LS3 is scheduled from 2026 to 2029 according to the [LHC long-term schedule](#).

the reconstruction of pixel tracks and vertices.

Once again, the usage of heterogeneous computing systems [181] is one of the strategies to mitigate this issue, following the successful Run 3 experience. Usage of distinct co-processors (such as GPUs), also referred to as accelerator devices, increases system performance and energy efficiency since tasks can be performed in a parallelizable way depending on the architecture of the co-processing unit.

This chapter describes the offline tracking algorithm used for the charged particles' reconstruction following the extensive description in Ref. [182], followed by a description of the HLT online tracks and pixel tracks reconstruction from Refs. [127, 183], and, finally, presents the modifications in the online heterogeneous pixel tracking algorithm to solve the issues mentioned in the end of Chapter 3, namely the lack of maintainability and the exclusivity to one type of accelerating device. These improvements are instrumental for the increased data acquisition rate during Run 3 and will continue to play a role during the HL-LHC era [114].

5.1 Offline Tracking Algorithm in CMS

The tracking algorithm's objective [127, 182] is to efficiently distinguish and reconstruct charged particles while keeping a low rate of "fake" tracks, i.e., tracks that were not correctly reconstructed either because the hits come from distinct particles or the track of a charged particle contains spurious hits.

Also, an important object to most, if not all, data analyses in CMS are vertices composed of the tracks of charged particles. Usually, they are used to define the most interesting pp collision, based on the scalar sum of the momentum of its constituents. However, needing to reconstruct on the order of 50 vertices per event is a challenging task. The reconstruction of tracks and vertices can be reduced to a combinatorial problem, where the tracks are sets of hits left by charged particles in the tracker sensors, and the vertices are sets of reconstructed tracks.

In general, the tracks and vertices reconstruction is composed of the following steps:

- Creation of digis (digitized data from detector electronics response) by unpacking raw detector information, where each digi represents one sensor of

the detector;

- Building of clusters of energy from nearby sensors, i.e., collections of digis;
- Association of clusters shape and digis charge to form particle hits by estimating their position and uncertainties;
- Building of n-tuplets, from collections of hits in distinct layers of the pixel tracker, and pixel tracks by fitting n-tuplets;
- Track building using pixel tracks as seeds;
- Track fitting to extract parameters;
- Vertex building from collections of tracks.

The tracking algorithm starts from the building of digis, clusters, and hits in what is called local reconstruction.

5.1.1 Local Reconstruction

The local reconstruction step involves clustering zero-suppressed signals that exceed customizable thresholds in pixel and strip channels to form hits, followed by calculating the clusters' positions and uncertainties.

Each pixel in the pixel detector's data acquisition system has an adjustable threshold for the sensors' readout [184], which is set to a level equivalent to a charge of 3200 electrons. During offline reconstruction, pixel clusters are constructed by combining adjacent digis [183], which are the unpacked and interpreted digitized information coming from the readout electronics. Each pixel that has a charge above the signal-over-noise threshold, mentioned above, is represented by a single digi that contains information about the position of the sensor in the column and row of a detector module and the collected charge.

Given their modular structure (that comes from the layout of the pixel detector), the process of creating digis can benefit from parallelization on two levels: different modules' information is processed in parallel by independent blocks of threads, while each digi is assigned a unique index and is processed by a distinct thread. Neighboring digis, including both first and second neighbors, are grouped to form clusters iteratively. A 2-D grid with the digis laid out by row, column, and unique index is created. Every digi is assigned to a different thread, and, in the case of neighboring digis, the one with the lower index is selected as the seed for the rest. At the end of the procedure, all digis will be assigned to a seed, which

will then receive a cluster index. The calculation of the clusters' information also benefits from parallelization, since each seed is assigned to a thread to perform this estimation.

Each cluster must have a minimum charge equivalent to 4000 electrons, where, as a reference, a minimum ionizing particle typically deposits about 21000 electrons. Corrections for residual charge miscalibration, variations in the charge injection capacitors used to calibrate pixel gain, are derived from laboratory measurements and integrated into the MC simulation. To calculate the position of pixel clusters, two algorithms are employed: a fast algorithm that is used in track seeding and pattern recognition; and a slower, but more precise, algorithm based on templates that is applied during the final track fitting.

In the fast algorithm, each sensor is assigned a coordinate system where the axes are parallel to the short and long sides of the pixels. The charge deposition happens in this 2-D space and the position of the hit of a charged particle is determined using the geometric position of the center of the cluster, the angle of the track concerning the plane of the sensor, the relative charge deposition of the two outermost pixels that are constituents of the cluster, and the geometrical width between the cluster second and second-to-last pixels [185], in both directions. In the x-axis, which is perpendicular to the CMS detector magnetic field, the Lorentz drift of the charges is also taken into account. The reasoning behind this choice is that it is expected that only part of the two pixels at the end to be covered by the traversing particle.

The slower but more precise algorithm is based on templates of charge deposition from charged particles, given that the significant radiation exposure experienced by the pixel detector throughout its operational lifetime substantially impacts charge collection by the pixels. This, in turn, degrades the performance of the standard hit reconstruction algorithm outlined above, as it relies only on the end pixels of clusters to calculate hit positions. In highly irradiated sensors, the reconstructed hit positions can exhibit biases of up to 50 μm , and the hit position resolution may worsen considerably. The template-based reconstruction algorithm addresses this issue by comparing the observed cluster charge distribution to expected simulated distributions, known as templates, to estimate hit positions [186].

To generate the templates, a large dataset of simulated particles traversing pixel modules is used. Those simulations are modeled with the PIXELAV simulation [187–189], which provides a very detailed replication of the working of the pixel sensors, taking into account the majority of the practical effects that are seen in reality. Because the PIXELAV program accurately describes the behavior of irradiated sensors, sets of new templates can be generated over the detector’s lifespan to preserve the hit reconstruction performance. To apply the template-based algorithm to tracks crossing the pixels at varying angles, separate sets of templates are created for different ranges of angles between the particle trajectory and the sensor. In the local coordinates of each sensor, the clusters are simulated in bins along both directions and are projected onto those directions in arrays of more pixels. The averaged measurement of the collected charge across all particles, and their root mean square (RMS), in these simulations is used to determine the distribution of a reconstructed track traversing the material, through minimizing the χ^2 function between the reconstructed cluster and the templates for each bin in a given sensor. The output of this procedure is one of the bins in the local coordinates where the particle is most likely to have hit. The uncertainty of the measurement also comes from the templates. Also, this χ^2 function is used to exclude outliers during track fitting, specifically, pixel hits on a track that are inconsistent with what is expected based on the angle of the reconstructed track.

The reconstruction of hits in the strip detector is, algorithmically, similar to the fast pixel hit reconstruction. Also, during Run 3, the local part of the procedure, that is, making the clusters, benefits from parallelization, given the modular geometry of this subdetector in a similar way to what was described above.

Zero-suppressed signals in the strip readout correspond to charge depositions five times larger than a given channel noise, or in the case where a strip and one of its neighbors’ charges exceed in two times the channel noise. Clusters are then seeded by zero-suppressed channels with a charge that exceeds three times the channel noise, and neighboring strips are added to a seed if their charge is twice the noise. If the total charge of a cluster is five times larger than the cluster noise, defined as $\sigma_{\text{cluster}} = \sqrt{\sum_i \sigma_i^2}$, where σ_i is the noise in each strip of a seed, the cluster is kept. The charge-weighted average of the strips’ position in a cluster is used to determine the hit position, where a correction due to Lorentz drift is applied. Typically, a function of the expected cluster width is used to parametrize the hit

uncertainty.

To estimate the performance of the hit reconstruction, the hit efficiency is used. This property is calculated as the probability of finding any cluster near an expected hit from a charged particle. In Figures 5.1 and 5.2, it is evaluated using 2022 data. The defective pixel channels are removed from the estimation. Figure 5.1 shows the BPix hit efficiency for all 4 layers as a function of the delivered integrated luminosity. It is possible to notice that the efficiency degrades with time, given the high amount of radiation experienced by this subdetector, which is evidenced by the large decrease in efficiency in the first layer. Periods of increase in the high voltage of the sensor or new calibrations restore the high efficiency in the pixel detector. In Figure 5.2, it is possible to see the behavior of the hit efficiency as a function of the instantaneous luminosity for all layers of the pixel subdetector, where higher luminosity worsens the efficiency.

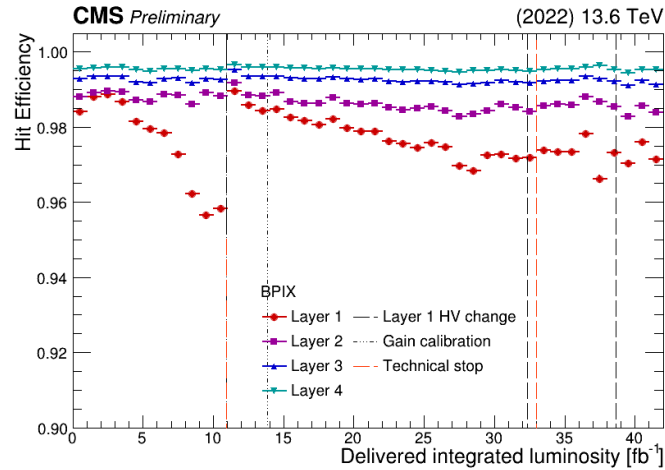


Figure 5.1: Hit efficiency in the four layers of the BPix subdetector as a function of the delivered integrated luminosity estimated using 2022 data. The vertical lines indicate changes in the first layer high voltage parameter (black, dashed line), periods of technical stop (red, dashed line), and calibration on the gain of the sensors (black, dash-dots line). Source [190].

A very similar approach is used in the strip detector, where the hit efficiency is measured as the fraction of charged particle tracks that left a hit anywhere in the module's active region. This measurement is also performed after removing the defective components of the strip detector. Figure 5.3 shows the hit efficiency as a function of the instantaneous luminosity for the TIB (left) and TOB (right) layers.

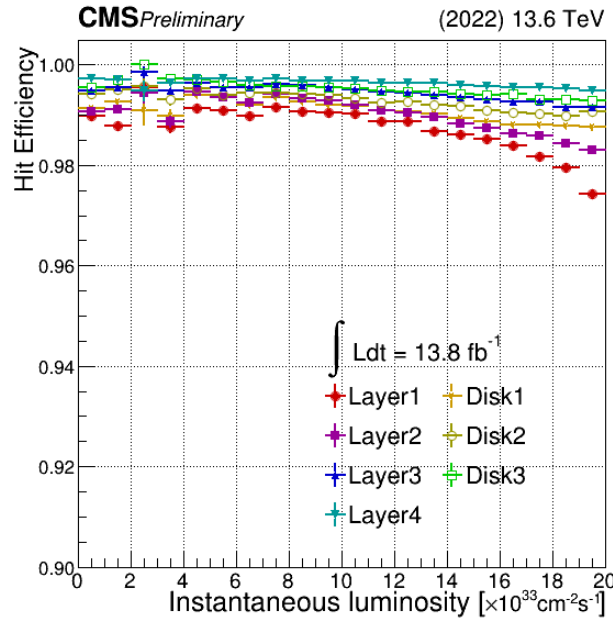


Figure 5.2: Hit efficiency in all layers of the pixel subdetector as a function of the delivered integrated luminosity estimated using 2022 data. Source [190].

Again, following the same trend observed in the pixel detector, the hit efficiency decreases as the instantaneous luminosity increases.

Another important metric of the quality of the hit reconstruction is the hit resolution, which is estimated from the hit residuals. The hit residual is calculated as the difference between the hit position that is measured and the hit's expected position that comes from the fitted track prediction. The resolution is then estimated from the RMS width of the distribution of the hit residual. To minimize biases, a refit of the trajectory is performed while not taking into account the hit under investigation.

In the pixel detector, both hit reconstruction methods mentioned above are used to extract the hit residuals and, consequently, the hit resolution for both. As can be seen in Figure 5.4, the resolution that comes from the template method is smaller, i.e., it is more resolved than the fast algorithm (named as generic reconstruction in the figure). The image shows the evolution of the resolution as a function of the delivered integrated luminosity, which gets progressively worse as the detector gets irradiated.

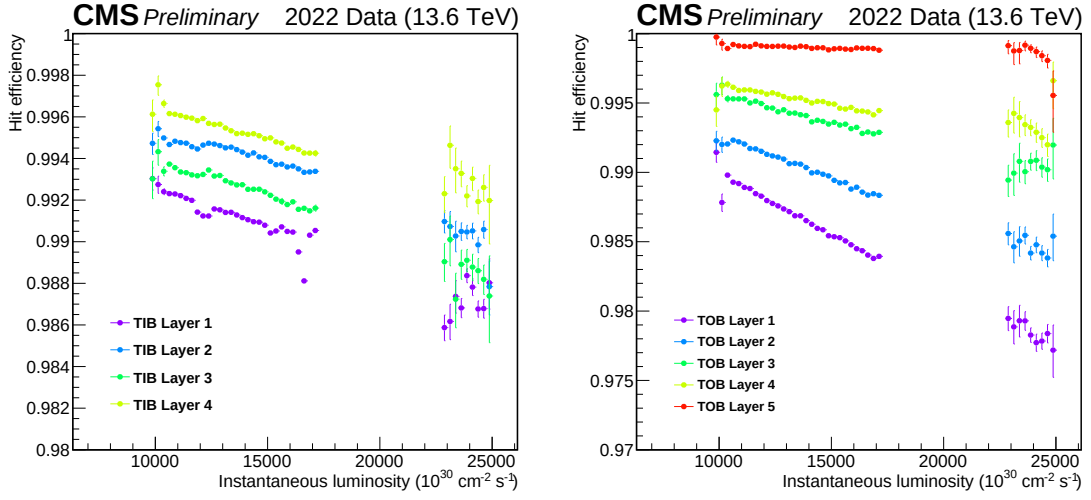


Figure 5.3: Hit efficiency in the four layers of the TIB (left) and five layers of the TOB (right) subdetectors as a function of the instantaneous luminosity estimated using 2022 data. The hit efficiency is measured for lower ($\sim 1.0 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ – $\sim 1.7 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$) and higher ($\sim 2.3 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ – $\sim 2.5 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$) instantaneous luminosity. Source [191].

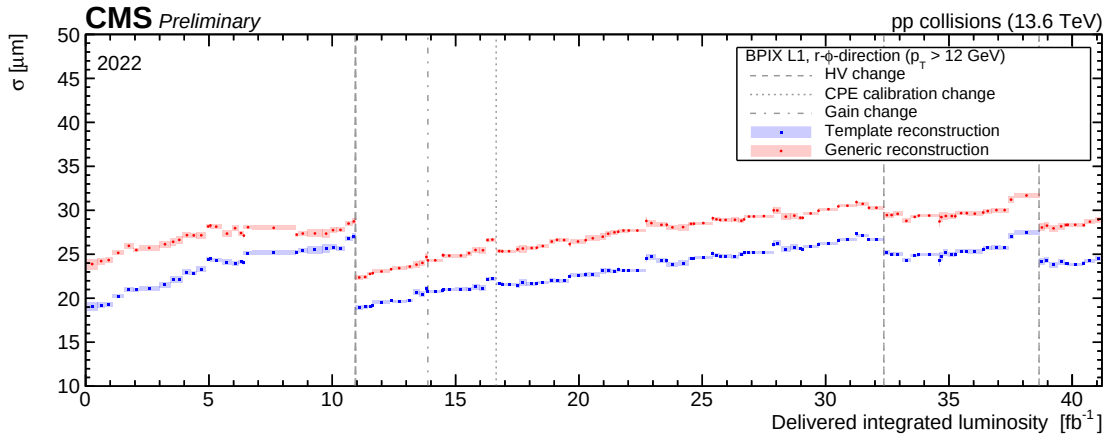


Figure 5.4: Hit resolution in the first layer of the pixel barrel subdetector as a function of the delivered integrated luminosity estimated using 2022 data. Source [190].

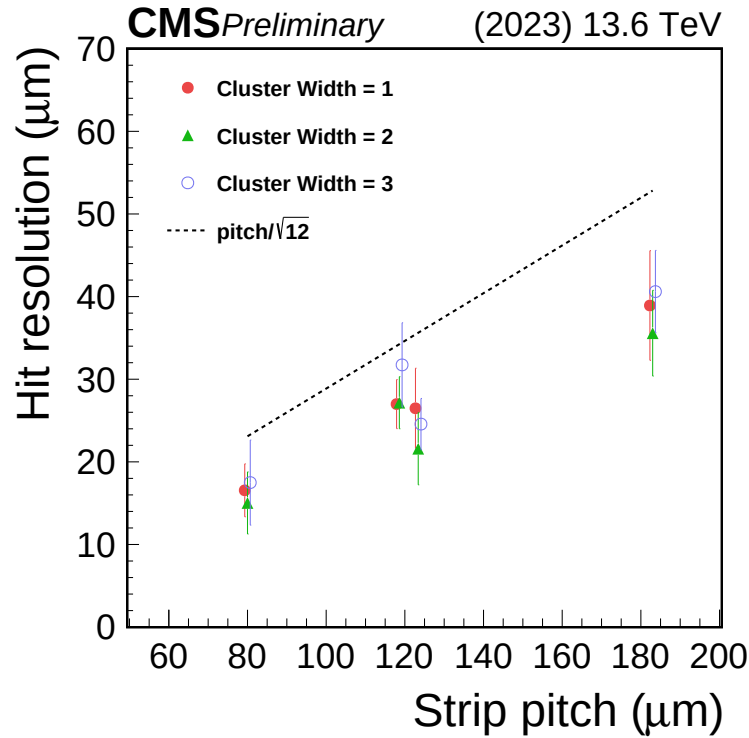


Figure 5.5: Hit resolution for distinct modules of the strip subdetector as a function of the strip pitch estimated using 2023 data. Source [193].

In the strip detector, multiple scattering typically results in track position uncertainties that far exceed the inherent resolution of the sensors. Consequently, individual hit residuals are not directly indicative of resolution. Despite that, a more precise measurement is the difference in a track's residuals for two closely spaced modules [192], as scattering-induced offsets are common to both modules. In that way, the difference in the measured hit positions is compared with the difference in the track's trajectory-predicted positions to obtain the residual distribution. The RMS width divided by $\sqrt{2}$ (to extract the resolution of a single module) is used to estimate the resolution. Figure 5.5 shows the hit resolution of the strip detector as a function of the strips' pitch and cluster size (width), which greatly affects the resolution.

5.1.2 Track Reconstruction

Tracking or track reconstruction is the process of using hits, obtained from the local reconstruction, to estimate the momentum and position parameters of

tracks, i.e., the charged particles' trajectories where the hits were deposited. A key aspect of this process involves translating from the hits' local coordinate system to the tracks' global coordinate system. This translation accounts for distinctions between the assumed and actual locations, as well as any surface deformations, of detector elements, which are determined through the alignment process [194]. Additionally, the local hit position intrinsic uncertainty will be incremented by the detector element location uncertainty.

Reconstructing charged particles' trajectories can be a very challenging task. In the environment of the Run 3 LHC collisions, on the order of hundreds to thousands of charged particles will need to be identified, reconstructed, and have their properties efficiently estimated in each event. In CMS, the software known as the combinatorial track finder (CTF) is used for tracking. It is an adaptation of the combinatorial Kalman filter [127, 195–197] (CKF), which is an extension of the regular Kalman filter algorithm [198] that allows for pattern recognition and track fitting in the same framework. The framework iteratively applies the CTF sequence in what is called iterative tracking. This procedure allows for the reconstruction algorithm to search and reconstruct tracks that are easier to identify at first, such as prompt (namely when charged particles are produced near the IP), higher p_T tracks, remove the hits from these tracks from the pool of hits available for track reconstruction and execute another iteration. Removing hits from previous iterations greatly reduces the complexity of the combinatorial problem, which implies the simplification of the next iteration. Consequently, the next iterations can search for more challenging trajectories, such as the ones that come from lower p_T and/or non-prompt charged particles.

In CMS during Run 3, thirteen iterations are used to reconstruct tracks, which are the following:

- Initial: target prompt, higher p_T tracks;
- LowPtQuad: used for prompt, lower p_T tracks;
- HighPtTriplet: reconstructs prompt, higher p_T tracks;
- LowPtTriplet: target prompt, lower p_T tracks;
- DetachedQuad: used for non-prompt tracks;
- DetachedTriplet: reconstructs non-prompt tracks;
- PixelPair: target prompt tracks;
- MixedTriplet: used for non-prompt tracks;

- PixelLess: reconstructs non-prompt tracks;
- TobTec: target non-prompt tracks;
- JetCoreRegional: used for high- p_T tracks in the dense environment of hadronic jets;
- MuonSeededStepInOut: muon tracks starting from the tracker;
- MuonSeededStepOutIn: muon tracks starting from the muon detector;

where each subsequent iteration is used to reconstruct different types of tracks not targeted by the previous iterations, such as lower p_T , more displaced tracks, using distinct seeding, etc. After every iteration, hits that come from the most well-fitted reconstructed tracks (which are found based on a selection, described below) are removed from the hits collection to ease the next iteration reconstruction.

Each iteration follows a four-step procedure:

- Seed generation: this step identifies initial track candidates using only 2 to 4 hits, providing the initial estimate of the track parameters with their uncertainties.
- Track finding: a Kalman filter is employed to extrapolate the seed trajectories to the charged particle's expected flight path. It searches for more hits that will be assigned to the track candidate.
- Track fitting: refines the trajectory parameters using both a Kalman filter and smoother.
- Track selection: quality flags are applied based on some of the track's parameters.

The main features that differentiate the iterations are how the seeds are generated and what the thresholds are for the track selection.

The initial track parameters and the uncertainties of potential charged particle trajectories are defined by seeds. The charged particles follow a helical path in CMS, given that they are traveling perpendicular to the magnetic field. Five parameters are needed to describe this trajectory: the particle's charge divided by its transverse momentum q/p_T ; the angle of the trajectory in the plane transverse to the beam spot² ϕ ; the angle of the trajectory with respect to the beam spot θ (or $\lambda = \pi/2 - \theta$), usually represented in terms of the pseudorapidity

²The beam spot is defined as the region in the center of the CMS detector where the proton beams will collide.

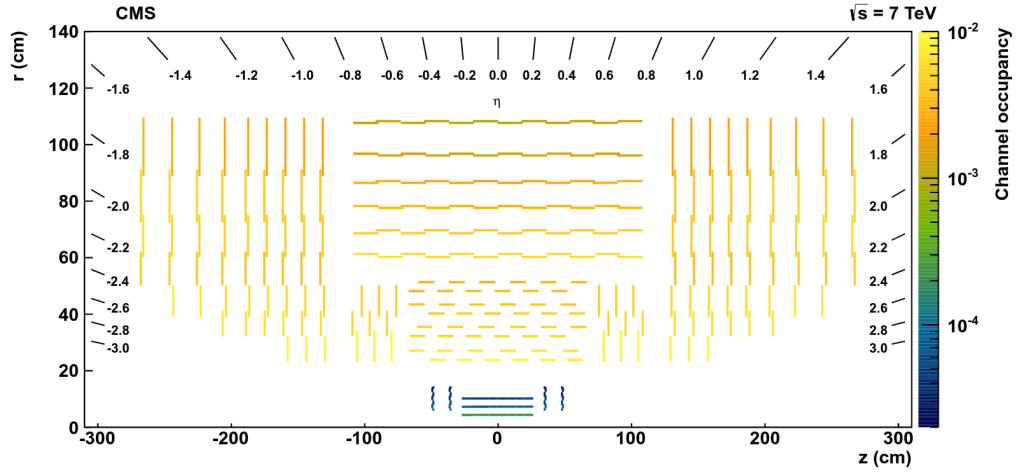


Figure 5.6: Occupancy of the channels in each module of the CMS tracker. The occupancy is shown for the layout of the pixel detector before the Phase-1 upgrade. Source: [182].

$\eta = -\ln(\tan(\theta/2))$; the transverse impact parameter with respect to the beam spot (or some primary vertex) d_0 ; and the longitudinal impact parameter concerning the beam spot (or some primary vertex) d_z . To estimate these five parameters, at least three 3-D hits are needed, or at least two 3-D hits plus a restriction on the track's origin, such as the assumption that it came from the beam spot (even though the tracker is made of, essentially, 2-D sensors, their distances to the beam spot are known, providing the third coordinate). Adding further constraints to the seeds limits the amount of hit combinations, decreasing the time to execute the next steps of the reconstruction. Requiring a minimum p_T or that the tracks come from the IP are examples of such restrictions.

A seed is usually generated from inward to outward in the tracks detector. This sounds counterintuitive since it could be expected that the outermost layers of the CMS tracker are less densely occupied by hits, given that the density of tracks in the pixel detector is factually higher. But in fact the opposite is true. Figure 5.6 shows the occupancy (fraction of channels with hits) of the whole CMS tracker. It is possible to notice that the occupancy is the lowest in the pixel tracker, because of its very high granularity, i.e., the number of channels that can perform a measure. Starting a seed from the inner layers of the tracker implies a better quality for the overall track.

The algorithm that generates seeds needs as input two main sets of parameters:

the so-called seeding layers and tracking regions. The former contains the pairs, triplets, or quadruplets of detector layers that have to be used to search for the hits, while the latter contains the requirements on track parameters to accept a candidate trajectory, such as the minimum p_T , the maximum transverse and maximum longitudinal distance of closest approach to the assumed production point, which is at the beam spot or a primary vertex. When a seeding layer is only composed of pairs of layers, hits from the two layers are used to reconstruct doublets that are only accepted as a seed if their track parameters pass the requirements set in the tracking region. For triplets or quadruplets of layers, the first step is still the reconstruction of hit doublets from the two innermost layers, followed by a search in the outer layers to find the next hits to build a hit triplet (and a hit quadruplet in the four-layer case). The seed is only accepted if the n -tuple (composed of n hits) track parameters pass the tracking region requirements.

The seeding strategy for each iteration takes into account the type of track that is targeted at the given iteration, and if it is possible to recover some of the lost efficiency from previous iterations. Table 5.1 shows the requirements of each iteration and their goal.

The JetCoreRegional iteration is used for the reconstruction of tracks inside high p_T jets. For this iteration, in particular, seeding faces a couple of challenges: the higher the jet p_T , the higher the amount of merged clusters on the first layer of the pixel barrel; also, the amount of candidate tracks and misreconstructed tracks increases with jet p_T . The approach to seed these tracks³ is to split the clusters using information about the jet direction to predict the cluster shape and charge that is expected.

To find the charged particle tracks from the seeds, the Kalman filter is used. It starts from the rough track parameters estimated from the seeds and iteratively updates these estimates by adding hits from successive layers of the detector. The position and uncertainty of the added hits, together with the amount of material crossed, are used to decide if a hit is to be added or not. The procedure to find a track is divided into four steps:

³This method changed in 2024. The new ML-based algorithm called DeepCore 2.0 Hybrid [199] is based on a combination of a deep convolutional neural network with the JetCoreRegional cluster splitting and has changed the way these clusters are found.

Table 5.1: CMS tracking algorithm iteration seeding strategy. The tracking region parameters for each iteration are also indicated. The superscripts [a], [b], [c], and [d] mean, respectively, consecutive layers, non-consecutive layers, hits can be missing in the innermost layers (obvious for the pixel+strip and strip-only seeding layers), and are used to recover efficiency from previous iterations. The units of p_T , R_{max} and z_{max} are [GeV], [cm], and [cm], respectively, with the exception of z_{max} for the four first iterations and PixelPair, which is given in terms of the number of standard deviations. The MixedTriplet and TobTec iterations have two sets of tracking region parameters to account for distinct track parameters and layer combinations.

Iteration	Seeding layers	p_T	R_{max}	z_{max}
Initial	pixel quadruplets ^[a]	0.5	0.02	4σ
LowPtQuad	pixel quadruplets ^[a]	0.15	0.02	4σ
HighPtTriplet	pixel triplets ^[b]	0.55	0.02	4σ
LowPtTriplet	pixel triplets ^[b]	0.2	0.02	4σ
DetachedQuad	pixel quadruplets ^[a]	0.3	1.5	15.0
DetachedTriplet	pixel triplets ^{[a][c]}	0.25	1.5	15.0
PixelPair	pixel doublets ^{[b][c][d]}	0.6	0.015	4σ
MixedTriplet	pixel+strip triplets ^{[b][c]}	0.4	1.5	15.0
	pixel+strip triplets ^{[b][c]}	0.6	1.5	10.0
PixelLess	strip triplets ^{[b][c]}	0.4	1.0	12.0
	strip doublets ^{[b][c]}	0.6	6.0	30.0
TobTec	strip triplets ^{[b][c]}	0.55	3.5	20.0
	strip triplets ^{[b][c]}	0.55	3.5	20.0
JetCoreRegional	pixel+strip doublets ^{[b][c]}	10.0	0.2	0.2
MuonSeededStepInOut	tracks from muons	-	-	-
MuonSeededStepOutIn	muons from muon chambers	-	-	-

- Navigation: determines, from the current track parameters and their uncertainties, what are the next layers that can be intersected by the extrapolated trajectory, by employing a fast analytical propagator assuming a uniform magnetic field and not taking into account multiple scattering or energy loss, which implies in a perfect helical trajectory for the track. The navigation is relatively straightforward in the barrel region but can be rather complex in the barrel-endcap transition regions.
- Search for compatible silicon modules: in the layers found in the previous step, a compatible module is set by checking if the position at which the extrapolated trajectory intercepts it is within a tolerance of three standard deviations of its boundary. Even though the propagation of the trajectory is

a complex and time-consuming task [200], the algorithm in CTF is optimized to keep the number of sensors to a minimum, while retaining almost 100% efficiency. As stated in Chapter 3, the CMS tracker contains overlapping sensors to provide full coverage around the IP, which means that particles cross multiple sensors when traversing those regions. Grouping the compatible modules in sets that do not contain overlapping modules is performed to address this issue.

- Hit grouping and refinement: all hits from each module group are collected, and "ghost hits" [182] are added to take into account material effects in defective modules, without giving a position information to the propagator. The combinatorial aspect of the tracking appears in this step, since for a given trajectory, multiple hits can be found to be good candidates to compose the track. The standard procedure is to only keep the hits that pass a χ^2 test with the prediction stage of the Kalman filter method.
- Trajectory updates: the track parameters are updated, including the newly added hit information.

This four-step process is repeated until a given condition is met, which can be distinct for each iteration. Also, other applications of the tracking algorithm, such as in the high-level trigger track reconstruction, can have distinct conditions to limit processing time. After the outward search is performed, an inward search using the trajectory information is applied, where its main purpose is finding additional hits that were missing from the seed, or that were not found during the pattern recognition phase. Lastly, a trajectory cleaning is performed, given that the same trajectory could come from distinct seeds, or that a seed could generate multiple trajectories. The cleaning is based on a fraction of the amount of shared hits by the track candidates. If it is higher than a set threshold, the candidate with more hits is kept, or the one with the lower χ^2 . This is done for all pairs of tracks in each iteration and in all pairs of tracks when the iterations are combined into one collection.

The process of track building described above is the most time-consuming step of track reconstruction since it is combinatorial in nature. Given the multi-threaded capability for data processing in Run 3, and that some of the used processors in CPU allow for single instruction, multiple data (SIMD) execution, a parallelized algorithm was developed for a great reduction in timing, while retaining physics performance. This procedure received the name of mkfit [201], and it works by

exploiting parallelization in three levels:

- Processing multiple events at once;
- The modular detector geometry is further split to have distinct regions processed in parallel;
- Collections of seed tracks are used in distinct threads to consider different groups of hits on each layer concurrently.

With this strategy, the algorithm is capable of advancing the global set of tracks layer by layer, until a given condition is met.

To avoid tail effects during parallelization, i.e., irregular workloads with distinct processing time, which implies in some threads to have to wait for the rest wasting processing time, the oneTBB is used, allowing for the tasks above to be divided into fine-grained tasks, while still being executed quickly due to the workload balancing through dynamic task "stealing".

The changes with respect to the track building steps defined above are the following: to reduce the size of data structures, global coordinates are used, where the hits are represented by the global position in the detector in Cartesian coordinates (x, y, z) , and the tracks are represented by $(x, y, z, \phi, \theta, 1/p_T)$, which are capable of deriving the five helical parameters described above; it uses a simplified detector description, with data structures that only contain the dimensions of each layer, layer indices, some parameters that are useful for track building, e.g., layer type and search windows for the hits, and control flags to perform track propagation; the navigation and search for compatible hits is performed analogously to those described above, while also taking into account material effects such as multiple scattering and energy loss; the branching of new candidates from the collection of compatible hits is performed in bins of pseudorapidity to allow for efficient hit information access and track concurrent processing, while employing techniques to avoid load imbalance due to distinct seeds generating distinct amounts of candidate tracks; finally, the cleaning of duplicate candidates is performed firstly based on the p_T , η and ϕ characteristics of the fitted tracks, which was tuned to retain track building efficiency in events with high PU, and then, after track building, using the same quantities with extra information about the hits in the track candidates.

Currently, not all tracking iterations benefit from the `mkfit` algorithm. The ones that use it are: `Initial`, `HighPtTriplet`, `DetachedQuad`, `DetachedTriplet`, and `PixelLess`, while the other iterations use the default CKF algorithm.

After the `mkfit` algorithm building, the next step is trajectory fitting. For this step, the full information of the track is only known when the last hit is found. However, this estimation of the track parameters can be rather biased by the assumptions and requirements made during track building, such as the beam spot constraint. A refitting procedure using the Kalman filter and smoother is then applied to improve the track candidates' parameter estimation.

The refitting starts by applying the Kalman filter at the innermost hit from the trajectory estimate. To minimize bias, the covariance matrix is scaled up significantly. The fitting then iterates through all hits outwards, updating the trajectory estimate with each hit, and the valid hits' position uncertainties are recalculated based on the current track estimation. After the refitting, the smoothing stage does the same procedure, but from the outermost hit inwards to the beam spot. A weighted average of both procedures' estimated parameters is associated with the tracks, providing the optimal track parameters, since, at every hit, it takes into account information from the previous and the next hits. The first and last hits are also included, since those can be propagated to the beam spot and calorimeters/muon chambers, respectively. This step also benefits from configurable parameters to improve processing speed, depending on where the tracking algorithm is being applied.

In regions with $|\eta| > 1$, the magnetic field is not very homogeneous. To account for these inhomogeneities, and, also, detector material effects, the filtering and smoothing process uses a numerical propagator that applies the fourth-order Runge-Kutta method to numerically solve the first-order derivative equations of motion of the particle for a given configuration of the magnetic field, since it may deviate from a perfect helical trajectory. This is only possible because of a very detailed and precise mapping of the magnetic field [202]. Trajectory estimates at other points can also be obtained by extrapolating the nearest hit's trajectory with this propagator.

Given the large amount of charged particles produced in an LHC collision,

the process described above produces a large amount of fake tracks, which are defined as reconstructed tracks that do not come from actual charged particles. To improve the quality of the tracks, a selection is applied over the collection of reconstructed tracks to separate those that are most likely to be tracks from real particles. This process evolved throughout the runs of CMS, starting as a set of criteria that tracks had to fulfill, moving to the application of a boosted decision tree using as input several characteristics of the reconstructed tracks, to what is currently used in the Run 3 that is a selection based on a deep neural network (DNN) [203]. The DNN uses information from the track parameters and their uncertainties, the number of valid and missing hits in the track, and the iteration flag, given that the score for assigning the quality of the tracks is distinct for the different iterations, and to be able to train the network over all iterations at once. Track quality is categorized into three levels, loose, tight, and high-purity, based on their efficiency and fake rate, both of which decrease with increasing quality. The DNN scores for the working points were chosen to match the efficiency of the previously used the boosted decision tree (BDT) method, while a great reduction in the number of fake tracks was achieved. After the selection step, the tracks from each iteration are combined into a single collection.

To evaluate the performance of track reconstruction, a set of important characteristics of the tracking algorithm is explored, e.g., the efficiency of reconstructing tracks, the fake tracks rate, and the duplicate rate. All of these characteristics are calculated as a function of the reconstructed track parameters to obtain the performance of the algorithm at the distinct regions of the tracks' parameter space. These calculations are performed using events from MC-generated samples, given that it is possible to know the true trajectory of the charged particles. It is also possible to control the events of interest to check the performance of the tracking in more relevant scenarios. The reconstruction efficiency is defined as the fraction of simulated tracks (originating from the main primary vertex) that are matched to a reconstructed track sharing over 75% of its hits. The fake rate is the ratio of reconstructed tracks not associated with any simulated track from any vertex. Using the same simulated tracks, the duplicate rate is defined as the fraction of simulated tracks matched to more than one reconstructed track.

In the figures below, the reconstructed tracks were chosen to have the high-purity quality flag. Figure 5.7 left shows the efficiency of tracking for the distinct

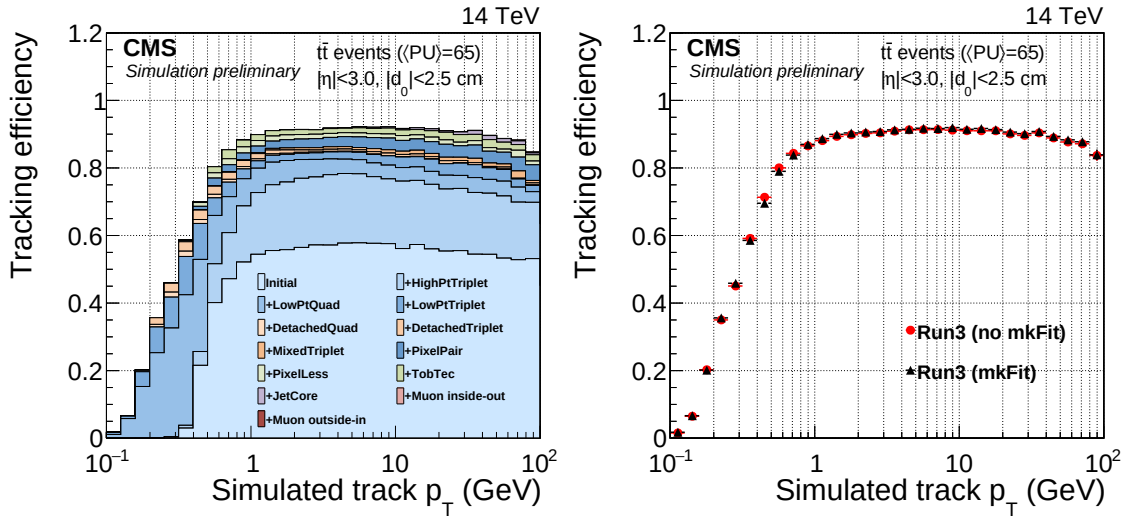


Figure 5.7: Tracking efficiency as a function of the simulated tracks p_T estimated with simulated $t\bar{t}$ events with an average PU of 65. Left: for the various iterations that compose the CMS tracking algorithm. Right: comparison between mkfit (black) and CKF (red). Source [201].

iterations as a function of simulated tracks p_T . It is possible to notice the effect of tracking region parameters in the plot, and how the iterations are complementary to each other. The plot on the right shows the impact of using the mkfit algorithm in the iterations mentioned above when compared to using the standard CKF algorithm. Given that the goal of the mkfit algorithm was to speed up the track-building stage, retaining the same efficiency is crucial. It is also possible to see a similar behavior in the plots of fake rate and duplicate rate as a function of the reconstructed track p_T displayed in Figure 5.8. As mentioned, the real gain of mkfit comes in the trajectory prediction time, shown in Figure 5.9. It is possible to notice a reduction of around 1.7 times in the time to build the tracks when using mkfit.

Figure 5.10 shows the comparison of the tracking efficiency when using the DNN or the BDT to perform track selection, as a function of p_T (left) and η (right), where, as mentioned above, the efficiencies should be comparable. Figure 5.11, however, shows the tracking fake rate comparison of using both selections, and it is possible to notice a substantial reduction in fakes when applying the DNN selection. In the duplicate rate, shown in Figure 5.12, a slight increase is observed for the DNN-selected tracks that come from merging mkfit and CKF tracks that were selected by the distinct DNNs (different DNNs were trained for mkfit and

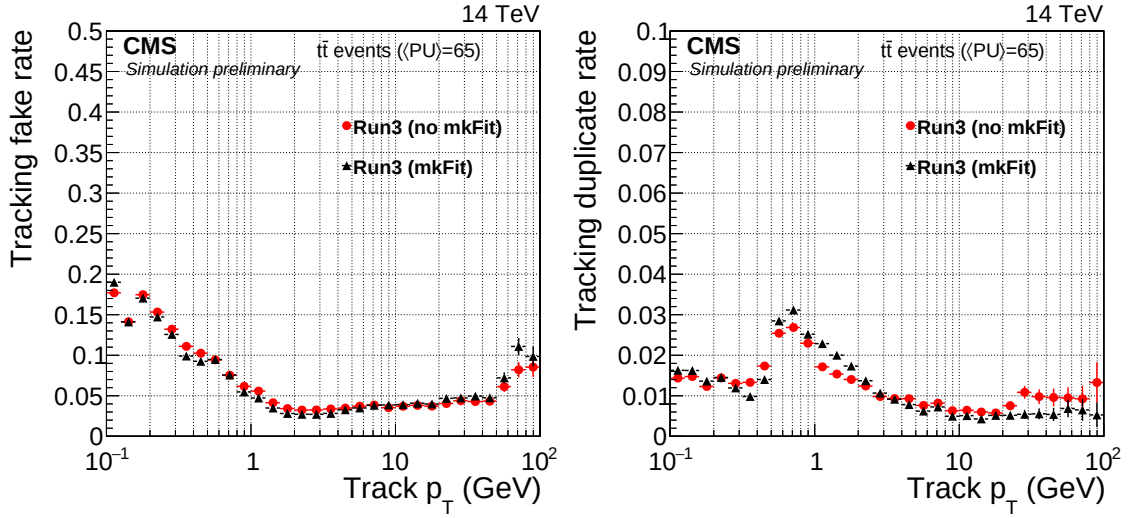


Figure 5.8: Tracking fake (left) and duplicate (right) rate as a function of the reconstructed tracks p_T estimated with simulated $t\bar{t}$ events with an average PU of 65. The CKF (red) and mkfit (black) are being compared. Source [201].

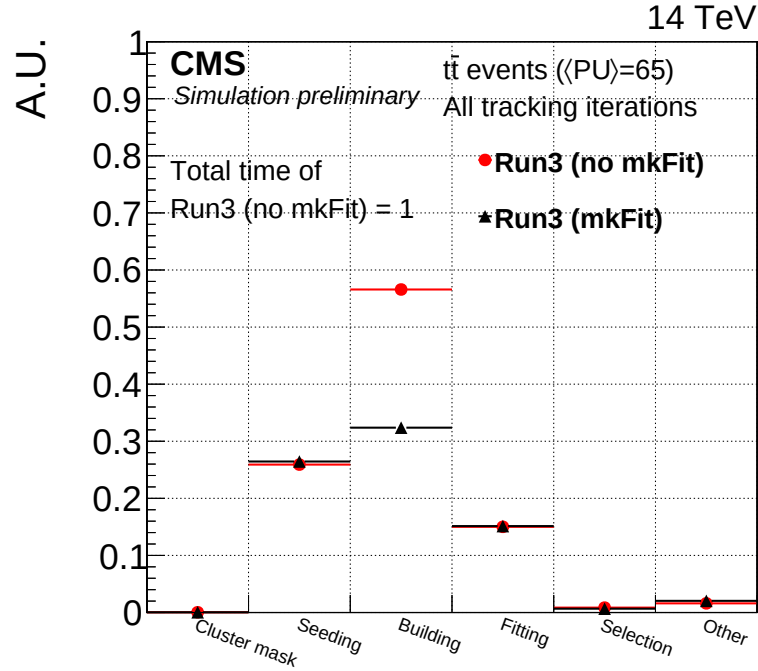


Figure 5.9: Timing comparison in between the stages of the tracking using the CKF (red) or the mkfit (black) algorithms estimated with simulated $t\bar{t}$ events with an average PU of 65. Source [201].

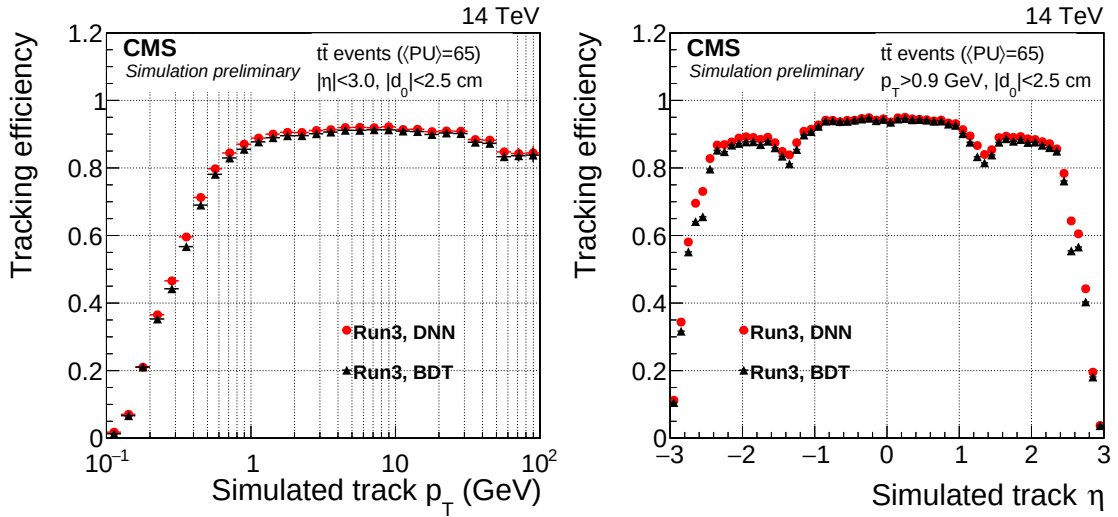


Figure 5.10: Tracking efficiency as a function of the simulated tracks p_T (left) and η (right) estimated with simulated $t\bar{t}$ events with an average PU of 65. The BDT (black) and DNN (red) are being compared. Source [203].

CKF tracks). Using the DNN also exhibits an improvement in timing to run the selection [204], where, when running with a batch size of only one, i.e., performing the classification of only one track at a time, it improves timing by 1.4 times, and when using a batch size of 16, the timing is substantially improved by a factor of 5.4.

5.1.3 Vertex Reconstruction

As mentioned at the beginning of this chapter, another object is produced based on information about the tracker: the vertices. The primary vertex reconstruction "builds" the regions from where multiple charged particles were produced, and provides the parameters of these objects, such as their amount of component tracks, location, p_T sum, and more.

The vertex reconstruction is composed of three steps: tracks' selection, the creation of groups of tracks that may come from a common vertex, and vertex fitting to extract its properties. The track selection is done based on requirements for its parameters. More specifically, it needs tracks where the normalized χ^2 is smaller than 10.0, the significance of the transverse impact parameter is less than 4.0, the minimum amount of pixel and pixel+strip layers with measurements is 2

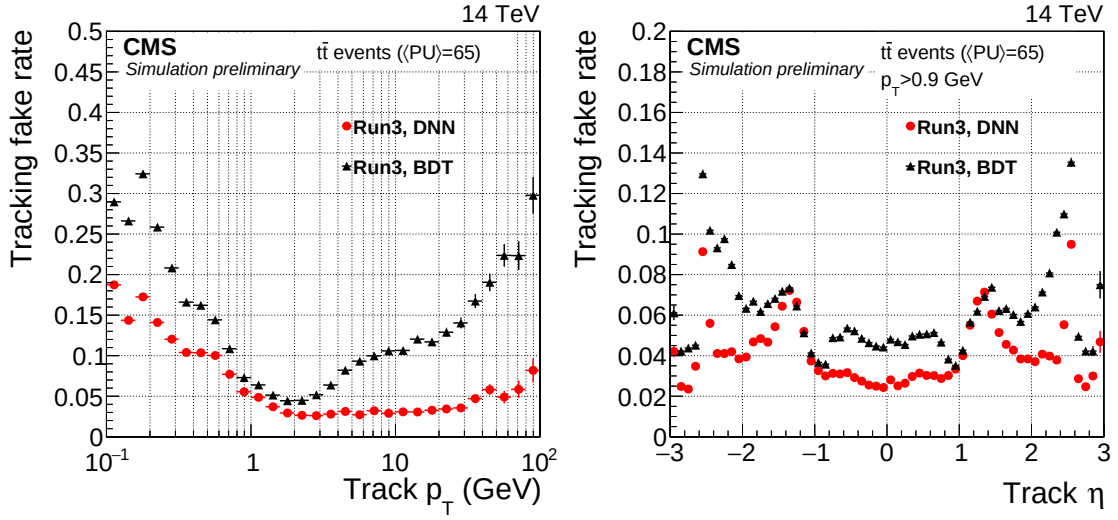


Figure 5.11: Tracking fake rate as a function of the reconstructed tracks p_T (left) and η (right) estimated with simulated $t\bar{t}$ events with an average PU of 65. The BDT (black) and DNN (red) are being compared. Source [203].

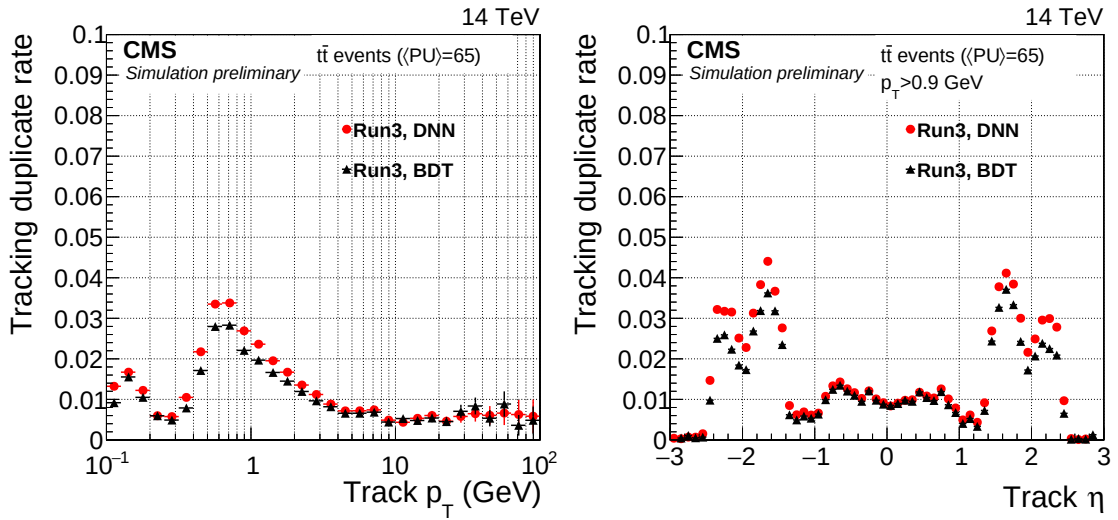


Figure 5.12: Tracking duplicate rate as a function of the reconstructed tracks p_T (left) and η (right) estimated with simulated $t\bar{t}$ events with an average PU of 65. The BDT (black) and DNN (red) are being compared. Source [203].

and 5, respectively, and no minimum p_T selection is applied.

Track clustering is performed using a deterministic annealing (DA) algorithm [205]. This method is well-suited for problems with many degrees of freedom, like assigning multiple tracks to multiple vertices. It works by mimicking the process of minimizing a system's free energy: starting at high "temperature" and gradually lowering it to reach a global minimum. What the algorithm needs is to sort tracks into vertices, where the tracks are weighted by p_{ik} , which is the probability for track i to be in vertex k . To fit the DA method, the analogy in the vertex reconstruction starts by defining the vertex χ^2 as the energy of the system, since, thinking about the possible states of the system, equal probabilities would mean equal χ^2 (or energy) for these configurations. Following the notation in Ref. [182], the free energy equation is given as:

$$F = -T \sum_i^{\text{\# tracks}} p_i \log \sum_k^{\text{\# vertices}} \rho_k \exp \left[-\frac{1}{T} \frac{(z_i^T - z_k^V)^2}{\sigma_i^{z2}} \right], \quad (5.1)$$

where T is the temperature, p_i are the track weights, which reflects their possibility of coming from the beam spot, ρ_k are vertex weights, which in this case of the mass-constrained clustering [205] follows $\sum_k \rho_k = 1$, z_i^T are track z positions with respect to the beam spot, σ_i^z are the track position resolutions and z_k^V are vertex z positions with respect to the beam spot, that is the variable of interest.

The algorithm's goal is to minimize F with respect to z_k^V at every new temperature while decreasing T . As the temperature diminishes, it gets closer to the "critical temperature" T_c of the current vertices, which means that the minimum of the energy gets to a saddle point. To go through this "phase transition" and continue decreasing the temperature, the vertex at T_c is divided into two nearby vertices, making sure that the ρ_k sum of these vertices equals the parent ρ_k , and the annealing proceeds. This procedure allows for the DA algorithm to begin with very high temperature (more specifically, above the first T_c) and only one vertex with uniform probabilities for all the tracks in the system to be assigned to it, and the decrease in temperature (with the constraint of minimizing the energy) is responsible for increasing the number of vertices and those to be optimally assigned to the tracks and vice-versa. Figure 5.13 shows an example of the DA algorithm working to find clusters of points in two dimensions. The method starts at a high temperature in image (a), which is decreased to find the points of phase

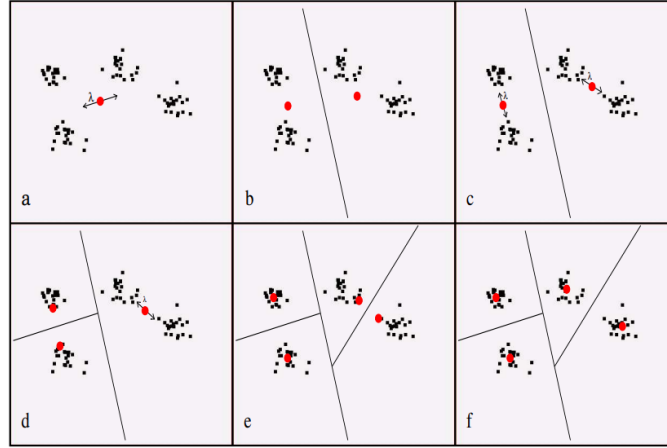


Figure 5.13: Scheme of the deterministic annealing algorithm. The parameter λ shown in the images is related to the T_c . Source: [206].

transition in images (b), (d), and (e). The method stops once it finds the best solution in image (f).

If the cooling goes on without truncation, that is, if $T \rightarrow 0$, a hard assignment of the tracks would occur, which means that each track would be assigned to exactly one vertex. In CMS, the technique used to avoid this is to limit the temperature at which the vertices are allowed to split at 2.0 since this provides a good trade-off between the possibility of splitting true vertices incorrectly and the resolving power. The temperature is still allowed to decrease after that for a better track assignment to the obtained vertices, given that it reduces the possibility of a track being assigned to multiple vertices. The minimum temperature of the algorithm is 0.5. This also improves the timing of the algorithm to be executed. From $T = 2.0$ until $T = 0.5$, an outlier rejection technique is used in the form of a cutoff on the tracks' assignment probability, pushing down the weight of the tracks that are separated from the nearest vertex by more than three standard deviations in the z -axis. Also, for a candidate vertex to be retained, at least two of its tracks must not be assignable to any other vertex. A method used to increase the throughput and efficiency of the DA algorithm, is to divide the input tracks into blocks of tracks, where distinct sets of tracks are selected based on their position in the z axis. This reduces the combinatorial problem needed to be solved by the algorithm, and allows the DA to be executed over the distinct block in parallel.

The retained candidate vertices are then fitted to extract their relevant proper-

ties, such as their position and uncertainties, the number of degrees of freedom, and tracks' weights. The method used for fitting is the adaptive vertex fitting [207], which assigns weights for the component tracks of the vertices, where the higher the weight, the higher the probability of that track truly belonging to the given vertex.

5.2 Heterogeneous Pixel Tracking

The offline events reconstruction is not the only place where tracking is used. The online events reconstruction, or, more specifically, the one that happens during the HLT selection, also makes use of the procedures described above, with some modifications, since it needs to be able to sustain the high rate of events selected by the L1T, while also retaining reasonable efficiency to be able to properly perform the events' selection.

The main differences concerning the offline reconstruction are: the usage of only one iteration during tracking, and that the vertices are produced using only pixel track information. The seeds for this iteration use triplets and quadruplets of pixel hits, where the local reconstruction of pixel and strip hits is analogous to the one described in Section 5.1.1, for track building and fitting it uses modified (faster) versions of CKF and the Runge-Kutta propagator, and it uses the Run 2 BDT approach for tracks selection and quality assignment.

With respect to tracking, the pixel tracking algorithms re-writing to fit a high-performance heterogeneous architecture, i.e., that makes it partially executable on GPUs, implied in a reduction of about 100 ms in the average time to reconstruct HLT events. The new algorithm became known as Patatrack [127, 183]. The Patatrack algorithm's local reconstruction was already described in 5.1.1. Tracks and vertices reconstruction are described below.

From the reconstructed hits, the first step in track building is the creation of doublets from adjacent layers, or skipping the layer in between, as shown in Figure 5.14. Given that the possible hit combinations in the pixel detector are very large, selections over the p_T , R_{max} , z_{max} , number of hits, and consistent cluster size in between the layers are applied to keep the processing time of this step as low as possible. Another choice that also improves on this matter is the grouping of

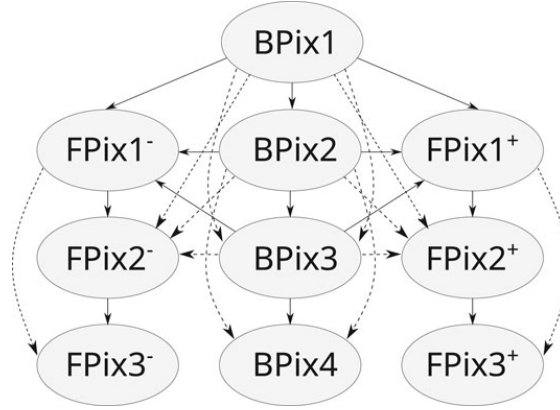


Figure 5.14: Possible layers that can form doublets. Full lines represent adjacent layers in the $r - z$ plane, while dashed lines represent skipping a layer in between the linked layers. Source: [183].

hits in regions of ϕ , limiting the window that each hit has to search for its pair. Finally, the outer hits search for a compatible hit in an inner layer follows all the constraints mentioned above. Each outer hit is assigned to a thread so that this search can be performed in parallel. The reduction in time that each choice above causes in the reconstruction of doublets is detailed in Ref. [183].

The next step is to combine the doublets into n-tuplets (at least three hits are needed for HLT pixel tracks). This procedure, algorithmically speaking, follows a cellular automata-inspired procedure [127, 208]. In this mathematical model, there exist simple structures, the cells, which are characterized by their states. The state of a cell evolves with time, and it depends on the initial state of the system it is embedded into and how it interacts with neighboring cells. In other words, there exists a set of rules to evolve the state of each cell from time $t - 1$ to time t , which is dependent on the state of neighboring cells in the system at time $t - 1$. What makes this philosophy suitable for n-tuplets reconstruction is that the state evolution of a cell only depends on the system's initial state, and it is based on local and simple calculations. These characteristics make the procedure highly parallelizable. The parallel with n-tuplets building is that the doublets described above are the cells of the system, and the set of rules to evolve the state of these cells, i.e., to extend the doublets, are the kinematic/geometric checks that are performed to link pairs of doublets that share a hit.

The rules that the cells follow to have their state evolved, i.e., getting linked

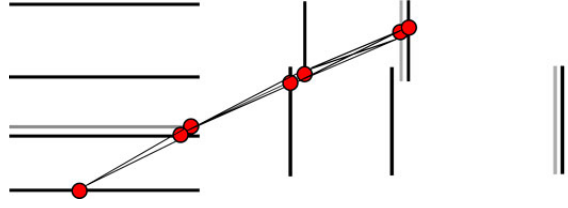


Figure 5.15: Scheme of fishbone n-tuplets. Source: [183].

to other cells, are the following: besides sharing a hit in a common layer of the pixel tracker, and coming from distinct pairs of layers, the three hits in neighboring cells must be aligned in the longitudinal plane ($R - z$), and follow a circle trajectory in the transversal plane ($x - y$) that is compatible with R_{max} , since the charged particles are subject to the magnetic field. All of the cells are tested in parallel to produce a graph of all the possible linked triplets. For the creation of quadruplets, the evolution of the cells' state is performed once more with the innermost layers. Afterward, a depth-first search (DFS) [209, 210] is applied to find quadruplets, which start from cells with the inner hit in the first layer of the pixel barrel detector (or in the second barrel or first endcap layers, to reconstruct outer triplets). A DFS search allows for the finding of each n-tuplet, which are performed independently of each other, making it possible to be executed on different threads.

The need to have a hermetic detector implies that some of the sensitive areas of the pixel detector layers overlap. This causes some layers of the pixel tracker to have more than one measured hit for a given charged particle, which, in turn, causes multiple cells to exist between two layers for the same track. To clean the possible doublets from these ambiguities, the fishbone n-tuplet algorithm [183] is applied during the building of the doublets. In this algorithm, for aligned cells sharing the same outermost hit, the shortest cell is kept. Figure 5.15 displays a scheme of fishbone n-tuplets. The light gray areas show modules with partial overlapping in that layer.

Finally, the found n-tuplets are fitted to extract the track parameters. The complete estimate of the parameters is divided into three distinct fits:

- A faster pre-fit in the $x - y$ plane to extract an estimate of the momentum of the track, that is then used to calculate the multiple scattering contribution of $\theta_{MS} \propto \frac{1}{p}$ [211];
- A line fit in the longitudinal plane to extract d_z and $\cot(\theta)$;

- And another circular fit in the $x - y$ plane to calculate d_0 , p_T and ϕ .

All of the n-tuplets are fitted concurrently in parallel using one thread per n-tuplet. After fitting, a duplicate remover algorithm is applied to retain only the best quadruplets (triplets) in the case where more than one quadruplet (triplet) contains the same doublet (hit). For quadruplets, the metric used is the smallest χ^2 of the fitted track, while for triplets it is the smallest d_0 .

With the pixel tracks, it is possible to build the pixel vertices, which follow a distinct approach from the one described in Section 5.1.3. This alternative approach is used because of the high throughput needed at the HLT. For pixel vertices, only quadruplets with $p_T > 0.5$ GeV are considered, which are then clustered to form the vertices. The clustering rule is based on the position of the tracks in the z axis (parallel to the beam direction), where, if the error in z of a track is lower than a set threshold, the density of tracks in its neighborhood, i.e., that are within a Δz_{cut} and have a χ^2 lower than a certain amount, is computed. If the density of a track is higher than one, it is set as a seed for producing a vertex. Starting from the seed tracks that follow the Δz_{cut} and χ^2 threshold are grouped to form the vertices, where a vertex is built if it contains at least two tracks. The characteristics of the vertices, such as the z position, χ^2 , and scalar sum of the p_T of its constituents squared $\sum p_T^2$, are computed during the vertex fitting procedure. Finally, the vertices are sorted by their $\sum p_T^2$. This algorithm is parallelizable at every step that is executed. Tracks' density is calculated for every track on different threads, tracks' grouping is also performed with distinct tracks at once, and the vertex fitting is done for many vertices in parallel.

5.3 Using the Alpaka Library

As mentioned in Section 5.2, the Patatrack algorithm was developed and deployed to exploit the full parallelizability when using CPUs+GPUs. Even though the Patatrack algorithm offered performance advantages, currently, the written code is duplicated. As previously mentioned, CMSSW modules and classes are written in the C++ programming language. To implement the reconstruction algorithms to be executed on the GPUs, the CUDA platform [212] (for NVIDIA GPUs) is used, where the modules call kernels to execute a given task on the GPU, and then the final product can be transferred back to the CPU. To be able to run the same algorithms also on different devices, the Patatrack reconstruction has

CPU functions and almost cloned GPU kernels that execute the same procedures on any device. This creates two issues: maintainability, since re-work is needed to account for all the distinct cases and the small differences between the CPU and GPU code can be difficult to work with; and the need for extra clones of the code for different devices, e.g., when using AMD GPUs that need the code to be written using the ROCm platform [213].

To solve this issue, performance portability libraries can be used. They allow for the code to be written only once, be executed on different devices/architectures, and retain close-to-native performance. One of such portability libraries is the Abstraction Library for Parallel Kernel Acceleration (Alpaka) [214–216] library, which is a header-only C++ library that provides performance portability across different back-ends, abstracting the underlying levels of parallelism. It supports serial and parallel execution on CPUs, and extremely parallel execution on GPUs. The goal was to port the Patatrack code using the Alpaka library to remove the duplicate implementation of the pixel tracking algorithm, thus reducing the maintainability required, while providing access to different devices that will be needed in the future. The porting of the code was performed in two steps: the change of the data structure layout in the CUDA code⁴, and the porting to Alpaka.

5.3.1 Porting to a Generalized Macro-Based SoA Layout

The first step was the implementation of a new structure of arrays (SoAs) for the parallel algorithms since they need to be optimized for coalesced memory access on the GPU; in other words, it is a format where the data occupy adjacent memory addresses, making the read/usage of the data more optimal, specially on GPUs. The new C++ macro-based SoA layouts [217] serve as templates for the data structures that can manage variable-sized arrays by assigning a size to the arrays at runtime. Those offer a generic object that can completely replace the multiple ad-hoc implementations that exist in CMSSW. Host and device-side classes can be created inheriting from the `Portable{Host|Device}Collections` using SoA layouts as templates. These classes take care of buffer allocation⁵ on the distinct devices and produce the SoA view mapping, which are pointers to each column in the layout.

⁴CUDA code here refers to the duplicated code needed to execute the reconstruction on both the CPUs and the GPUs.

⁵The buffer knows what device the memory is on, and how to free it when it is not needed anymore.

In CMSSW, the main data formats that are components of the pixel tracks and vertices reconstruction are the following:

- SiPixelDigis
- SiPixelCluster
- TrackingRecHit
- Track
- Vertex

where each contains the SoA for the distinct objects. For each object, the changes in the SoA would be similar to the `Track` example in Figure 5.16, and distinct classes for host- and device-side memory allocation are created.



```

class TrackSoAHeterogeneousT {
private:
    eigenSoA::ScalarSoA<uint8_t, S> quality_;

public:
    eigenSoA::ScalarSoA<float, S> chi2;
    eigenSoA::ScalarSoA<int8_t, to S> nLayers;
    eigenSoA::ScalarSoA<float, S> eta;
    eigenSoA::ScalarSoA<float, S> pt;
    // More statements follow
}

GENERATE_SOA_LAYOUT(TrackSoALayout,
    SOA_COLUMN(Quality, quality),
    SOA_COLUMN(float, chi2),
    SOA_COLUMN(int8_t, nLayers),
    SOA_COLUMN(float, eta),
    SOA_COLUMN(float, pt),
    SOA_EIGEN_COLUMN(Vector5f, state),
    SOA_EIGEN_COLUMN(Vector15f, covariance),
    SOA_SCALAR(int, nTracks),
    SOA_SCALAR(HitContainer, hitIndices),
    SOA_SCALAR(HitContainer, detIndices))

```

Figure 5.16: Modification done from "old" SoA (left) to "new" SoA (right) layout. Shown is the example for the `Track` data format, but a similar approach was performed for each object.

Besides the changes in the data formats, due to differences in how the arrays were being accessed in each of the SoA layouts, mainly because the layouts wrap the SoA view which is used to access the objects of the SoA, anywhere the objects were used had to be modified to access its variables through the view. One such example is in Figure 5.17, which shows how objects are accessed before and after porting the data formats to the generic SoA templates.

The reconstruction code is divided as follows (using the naming as they are in CMSSW):

- `RecoLocalTracker/SiPixelClusterizer`: detector raw information unpacking into digis and building of clusters

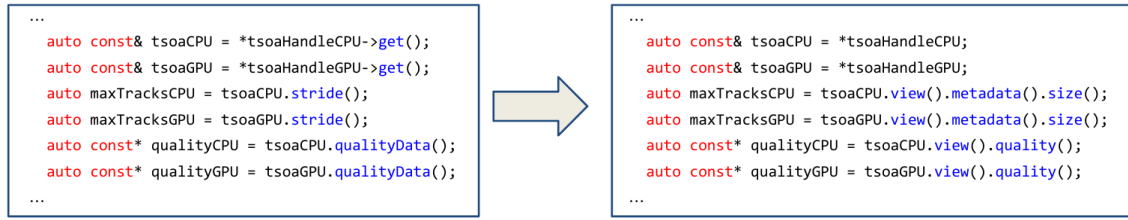


Figure 5.17: Modification done to access the objects inside the new SoA layout from the wrapped view. Shown is the example for accessing objects in the `Track` data format, but a similar approach was performed for every other object.

- `RecoLocalTracker/SiPixelRecHits`: building of hits using digis/cluster information
- `RecoPixelVertexing/PixelTriplets`: creation of n-tuplets and consequently tracks from hits with the track fitting procedure to extract track parameters
- `RecoPixelVertexing/PixelVertexFinding`: building of vertices from collections of tracks

Other modifications had to be done, mainly in directories containing plugins to convert data stored in the accelerator device to data in the host CPU (`EventFilter/SiPixelRawToDigi` and `RecoPixelVertexing/PixelTrackFitting`, which also produce the legacy data format that is used for offline data analysis), the data quality monitoring utilities for the pixel tracks (`DQM/SiPixelHeterogeneous`), and the plugins that generate the seeds for the full tracking (`RecoTracker/TkSeedGenerator`).

Concurrently with these changes, the inclusion of templates to take into account distinct tracker configurations/geometries and tracking algorithms was ongoing. The main changes occurred in the data structures in which the whole pixel tracker topology/geometry was being defined (`Geometry/CommonTopologies`) to include both the pixel tracker Phase 1 and Phase 2 geometries and parameters.

All the modifications to CMSSW and the discussions/reviews about this first stage can be seen in Refs. [218, 219]. To evaluate the performance of the modified pixel tracks' reconstruction code, two methods were used: checking the throughput, i.e., the number of events per second that were reconstructed, and comparing the reconstructed object efficiency and fake rate concerning its properties.

In Figure 5.18, it is possible to see the comparison in the throughput of the original code (in blue) and the modified code (in red) concerning the number of streams⁶, and both are in agreement. The same can be said about the pixel tracks' efficiency and fake rate as a function η , ϕ , and p_T . Figure 5.19 shows the efficiency and fake-rate comparison of pixel tracks being reconstructed with the old code on the CPU (blue) or GPU (red), with pixel tracks being reconstructed with the new code on the CPU (black) or GPU (orange). No changes were expected in any of these checks for this first step.

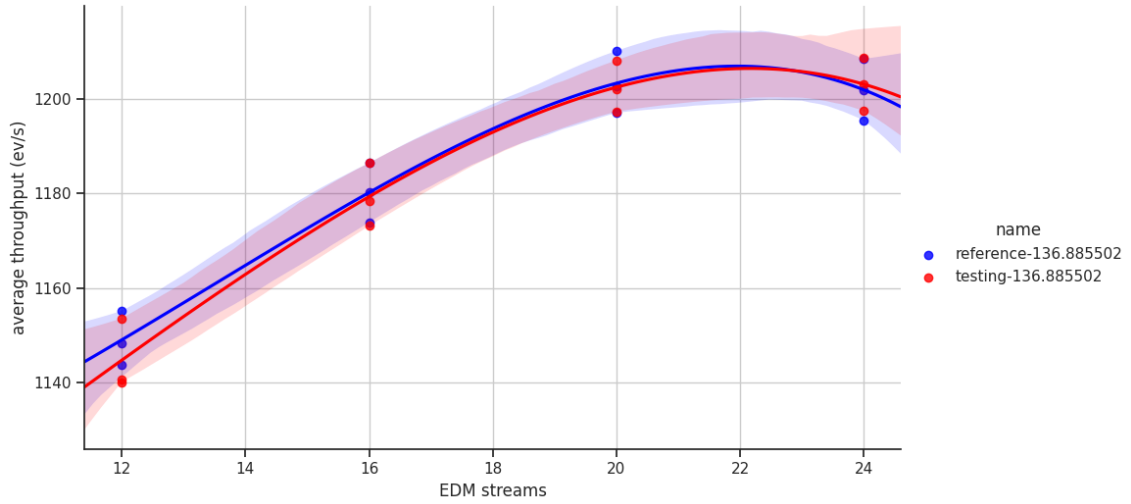


Figure 5.18: Throughput comparison of reconstruction using old code (blue) with modified code (red), as a function of the number of streams. The throughput was calculated using data from a 2018 run. No differences were expected.

5.3.2 Porting to Alpaka

Besides extra changes to the data formats, needed due to differences in the workings of the `PortableCollections` for the Alpaka code⁷, the CMSSW framework classes to execute a given task were also modified. Specifically, new `ESProducer`, which produce the event setup conditions, and `EDProducer`, which produce the event data information, were implemented to work with the Alpaka collections. This change, together with modifications in the input/output data to the modules, and distinct formats to the data dictionaries (mainly to inter-

⁶Each stream can run the reconstruction modules over a few events, assigned automatically by the CMSSW framework, and are independent of each other. They are executed concurrently.

⁷Alpaka code here refers to the code needed to execute the reconstruction on both the CPUs and the GPUs, written only once and compiled for distinct devices

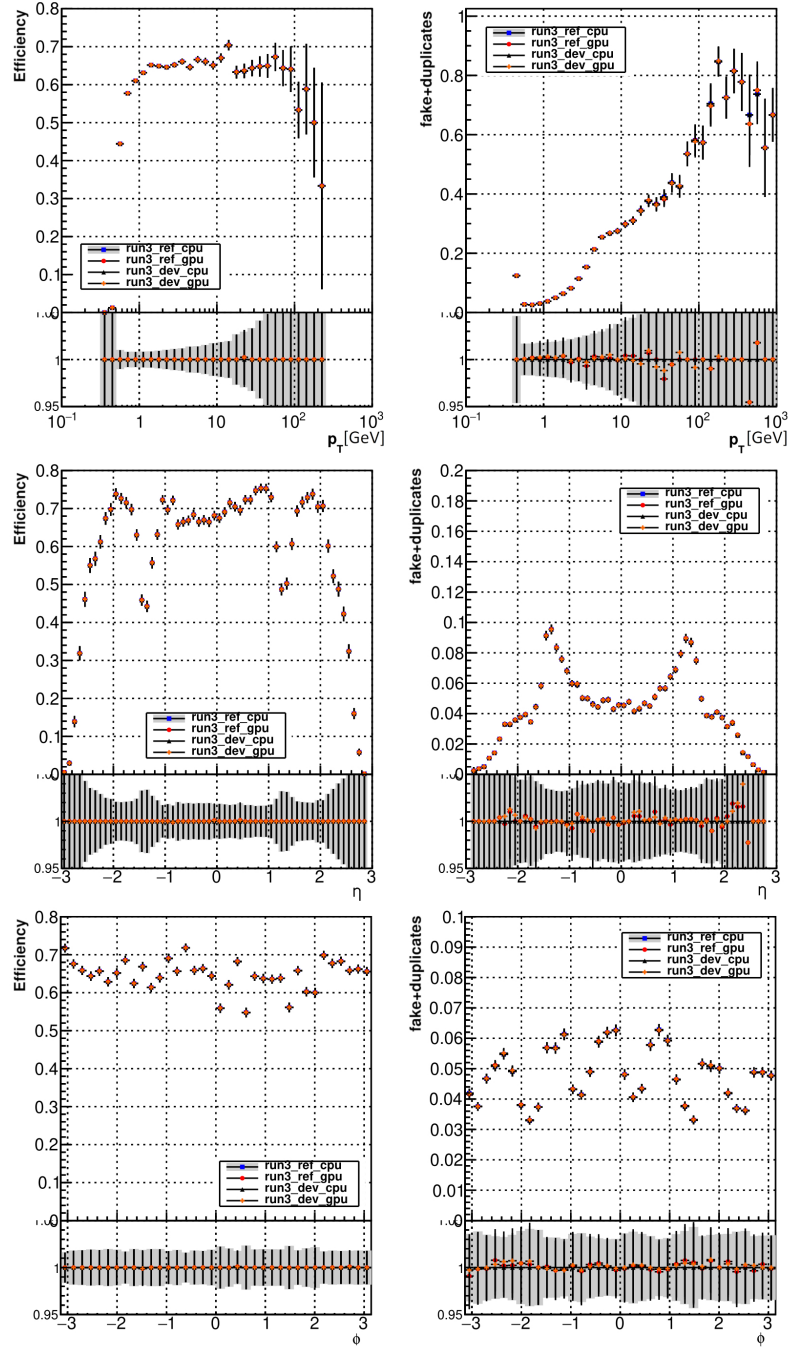


Figure 5.19: Comparison of pixel tracks being reconstructed with the old code on the CPU (blue) or GPU (red) with pixel tracks being reconstructed with the new code on the CPU (black) or GPU (orange). The efficiency and fake rate were estimated using a Run 3 simulation of $t\bar{t}$ processes with an average PU of 65. No relevant differences were expected.

face the produced data with the ROOT framework [220]), implied that the majority of the Patatrack reconstruction code had to be rewritten/updated.

The indication for the framework of when to compile the code for the distinct devices came from the addition of alpaka folders [221], where the Alpaka plugins needed to be included, following the changes as displayed in Figure 5.20.

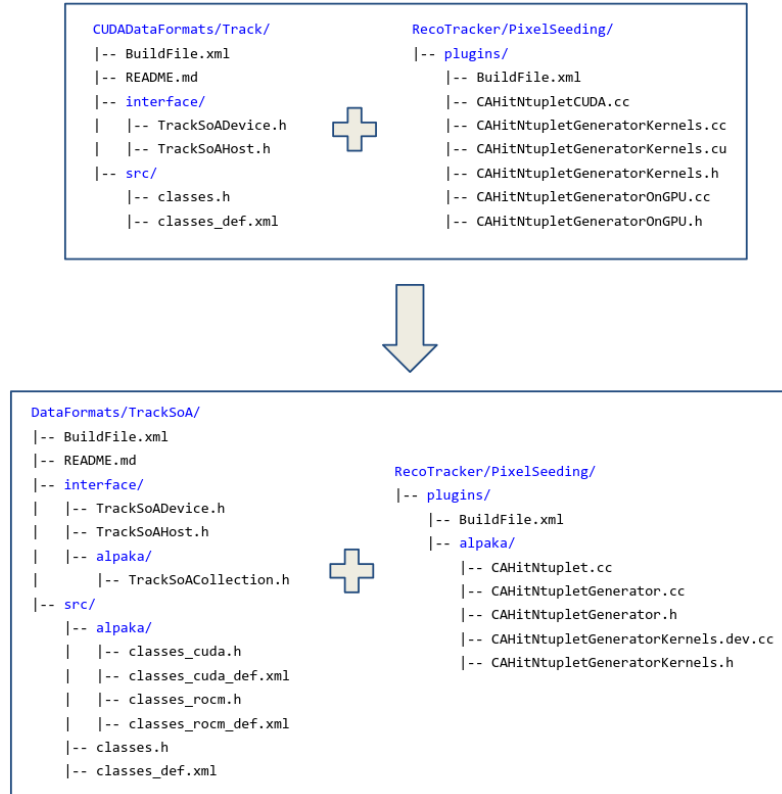


Figure 5.20: Example of changes in file structure for Alpaka. Files have been omitted to not pollute the image with unnecessary information. Main modifications are the inclusion of the alpaka folder that contains all the code to be compiled for distinct devices, new class dictionaries to take into account objects created by distinct devices, and, using as an example the CUDA code, the kernels that do the reconstruction are now contained in *.dev.cc files.

Besides the main data formats for pixel tracks, some extra objects needed to be included, given that all of the inputs also needed an Alpaka counterpart:

- BeamSpot
- SiPixelClusterSoA
- SiPixelDigiSoA

- TrackSoA
- TrackingRecHitSoA
- Vertex

The created/modified directories for the rest of the reconstruction algorithm were the following (using the CMSSW naming):

- CalibTracker/Records: building of event setup records for tracker mapping/gain calibration
- CalibTracker/SiPixelESProducers: producing event setups for tracker mapping/gain calibration
- CondFormats/SiPixelObjects: data formats for pixel tracker mapping/gain calibration
- Configuration/ProcessModifiers: addition of an alpaka modifier to run the pixel tracks reconstruction with the Alpaka code
- RecoLocalTracker/SiPixelClusterizer: detector raw information unpacking into digis and building of clusters
- RecoLocalTracker/SiPixelRecHits: building of hits using digis/clusters information
- RecoTracker/PixelSeeding: creation of n-tuplets and consequently tracks from hits
- RecoTracker/PixelVertexFinding: building of vertices from collections of tracks

To be able to check the performance of the Alpaka code and to compare it with CUDA, two versions of the CUDA code were used: the CMSSW version with the CUDA-only implementation of the reconstruction algorithm and the updated CMSSW that also contains the Alpaka modifications. This was needed, since maintaining the CUDA code in CMSSW for some time allowed for more cross-checks to be performed, and the performance of the distinct versions to be compared thoroughly. The efficiency and fake rate plots in Figure 5.21 compare pixel tracks pseudorapidity after being reconstructed on the CPU and GPU with the CUDA-only code (blue and orange, respectively), and with the Alpaka code (green and red, respectively). In Figures 5.22 and 5.23, a comparison of the objects reconstructed on the CPU and the GPU using the Alpaka code is performed. Figure 5.22 shows the number of pixel tracks being reconstructed on the CPU vs on the GPU for the CUDA-only version (left) and the Alpaka version (right). Similarly, Figure 5.23 shows the amount of pixel vertices being reconstructed on the CPU

vs on the GPU for the CUDA-only version (left) and the Alpaka version (right). No changes were expected in any of these checks for this second step, as can be seen by the almost perfect agreement in the comparisons. All the modifications to CMSSW and the discussions/reviews about this second stage can be seen in [222–229].

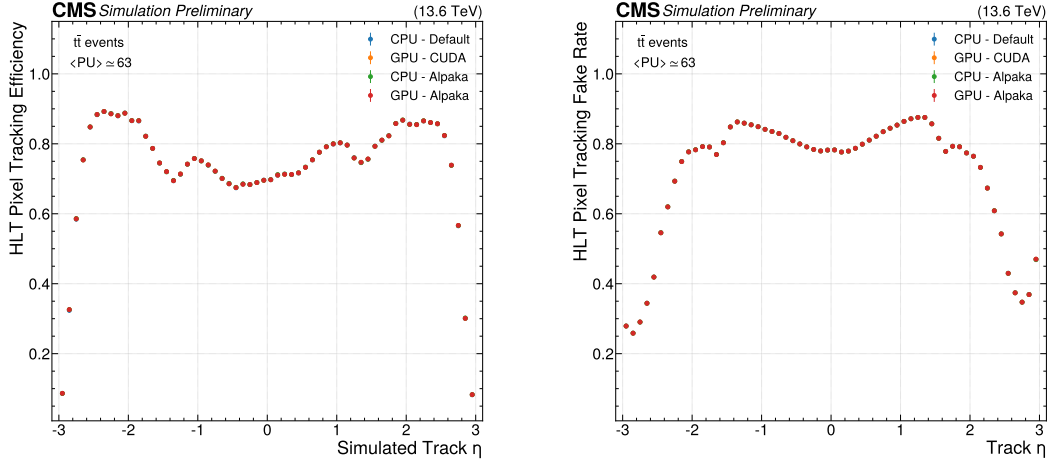


Figure 5.21: Comparison of pixel tracks efficiency and fake rate as a function of η , for tracks reconstructed with the CUDA-only code on the CPU (blue) and GPU (orange), and the Alpaka code on the CPU (green) and GPU (red). These variables were estimated using a Run 3 simulation of $t\bar{t}$ processes with an average PU of 63. No relevant differences were expected. Source [230].

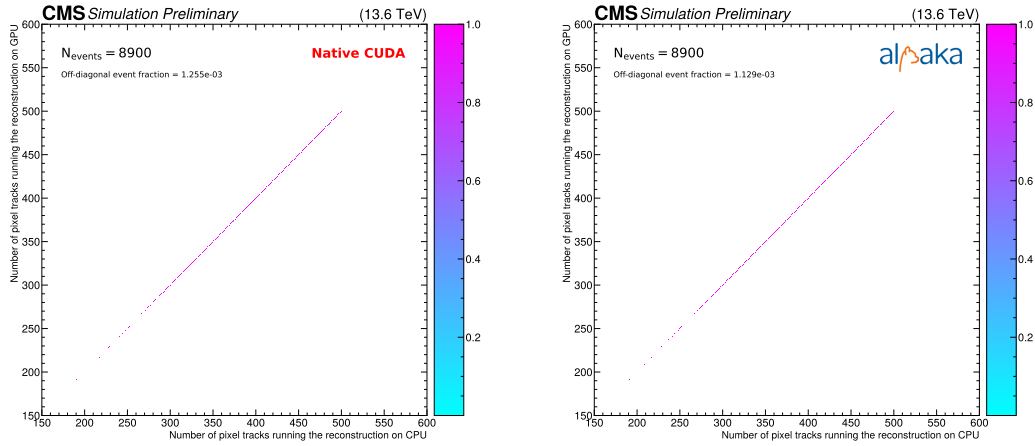


Figure 5.22: Comparison of the number of pixel tracks reconstructed on the CPU vs on the GPU for tracks reconstructed with the CUDA-only code (left) and the Alpaka code (right). No relevant differences were expected. Source [230].

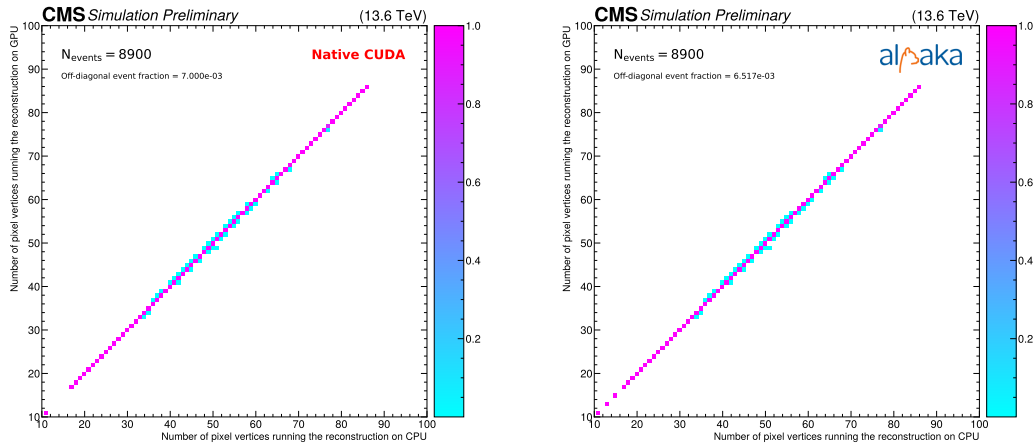


Figure 5.23: Comparison of the number of pixel vertices reconstructed on the CPU vs on the GPU for vertices reconstructed with the CUDA-only code (left) and the Alpaka code (right). No relevant differences were expected. Source [230].

Besides aiding in the data acquisition for the disappearing tracks analyses in the near future, these changes benefit the CMS collaboration as a whole. Even though an improvement in efficiency or timing is not observed, or expected, its impact in the flexibility on the development of new algorithms for data processing and the acquisition of more computing power, in terms of obtaining different types of processing units from distinct manufacturers, will improve the capability of the collaboration to collect and analyze data.

Chapter 6

Search for Disappearing Tracks with CMS Early Run 3 Data

As discussed in Chapter 4, previous CMS analyses investigated disappearing tracks using 19.5 fb^{-1} of 8 TeV, 38.4 fb^{-1} of 13 TeV, and 101 fb^{-1} of 13 TeV pp collision data collected in 2012 [136], 2015–2016 [137], and 2017–2018 [138], respectively. These searches excluded, at the 95% confidence level, the direct electroweak production of wino-like charginos with a mass below 884 (474) GeV for a mean proper lifetime of 3 (0.2) ns. In this search for disappearing tracks, the events analyzed are from 62.5 fb^{-1} of collected data in 2022 and 2023 at $\sqrt{s}=13.6 \text{ TeV}$.

To identify candidate disappearing tracks, events are initially required to include an isolated, high- p_T track. This track must not be consistent with a SM charged lepton. Additionally, candidate tracks must exhibit minimal associated energy deposits in the calorimeter and have multiple missing outer hits in the silicon tracker, characteristic signatures of disappearing tracks from signal processes. In contrast, tracks arising from background (BG) SM processes generally display either few missing outer hits or large associated calorimeter energy deposits, as shown in Figure 6.1. Standard model processes yield a disappearing track signature only when a misreconstruction occurs, such as an electron's energy not being fully registered by the electromagnetic calorimeter. These background contributions are evaluated using data-driven methods. MC signal events are produced following the workflow described in Chapter 4. The methodology to evaluate the sensitivity of the search is the "cut and count", which is based on a series of requirements applied over the analyzed events to select relevant ones that increase the signal over background significance.

Besides the signal simulation, data sets and triggers used in the analysis, described in Chapter 4, this chapter describes the remaining parts of the data analysis:

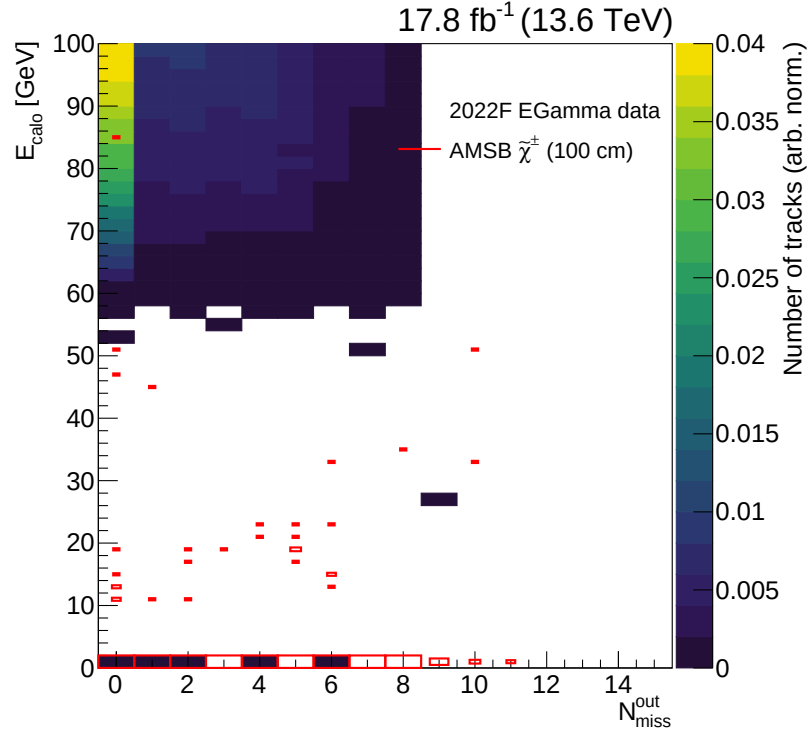


Figure 6.1: E_{calo} vs $N_{\text{miss}}^{\text{outer hits}}$ for tracks in the $n_{\text{layers}} = 6+$ search bin. Colored bins represent the distribution of events from an electron-dominated control region using data from 2022F. Empty red boxes represent the generated AMSB charginos distribution, where the size of the boxes reflects the relative number of events in a given bin. The charginos produced are wino-like with $m_{\tilde{\chi}_1^\pm} = 700 \text{ GeV}$ and $c\tau = 100 \text{ cm}$. These variables are the most discriminative of the disappearing tracks search, as can be seen by the explicit separation between SM and BSM. It is possible to notice that SM events are clustered at small $N_{\text{miss}}^{\text{outer hits}}$, mostly at 0, and $E_{\text{calo}} > 50 \text{ GeV}$, while BSM events are more distributed over $N_{\text{miss}}^{\text{outer hits}}$, while the E_{calo} is, in the majority of events, close to 0.

the definition of the objects used is given in Section 6.1, that is used in all of the search; Section 6.2 details the criteria used to select disappearing tracks events; the two main sources of background events are described in Section 6.3, with the estimated number of BG events from collected data being shown; Section 6.4 shows the MC to data corrections applied over signal samples; all of the background and signal number of events estimation have their systematic sources determined in Section 6.5; and, finally, Section 6.6 compiles all of the estimated number of BG and signal events, along with their systematic uncertainties, to be used in the cut and count statistical method and extract results.

In the search for disappearing tracks, several requirements are applied over the data to separate events into the signal region. The objects used in the analysis have to be selected following the central guidelines from CMS for data analysis to ensure the best possible performance. These objects are: p_T^{miss} , jets, electrons, muons, hadronic taus, primary vertices, and charged particle tracks.

6.1 Object definitions

Whenever p_T^{miss} is used, PF p_T^{miss} with type-1 corrections¹ applied is employed, and the p_T of all reconstructed muons is counted as invisible, denoted by $p_T^{\text{miss, no } \mu}$. This approach ensures consistency between the offline p_T^{miss} and the calorimeter-based p_T^{miss} used in the triggers, both at L1 and HLT. When jets are used, they refer to PF jets with $p_T > 30$ GeV and $|\eta| < 4.5$, reconstructed using the anti- k_T clustering algorithm [232, 233] with a distance parameter of $R = 0.4$ and with charged hadron subtraction [234] applied (AK4 jets)². Muons, electrons, and hadronically-decaying tau leptons (hadronic taus, also referred to as τ_h) are reconstructed using the appropriate PF algorithms [178].

Given the use of missing transverse momentum in this search, a set of standard p_T^{miss} filters, recommended by the CMS collaboration experts, is applied to elimi-

¹The type-1 corrections [231] take into account the jet energy scale corrections in the calculation of the p_T^{miss} following:

$$\vec{p}_T^{\text{miss corr}} = \vec{p}_T^{\text{miss}} - \sum_{\text{jets}} (\vec{p}_{T, \text{jet}}^{\text{corr}} - \vec{p}_{T, \text{jet}})$$

where "corr" refers to the values after corrections.

²The charged hadron subtraction algorithm works as a PU mitigation technique. More advanced methods exist, such as the pileup-per-particle identification (PUPPI) [235].

nate events with poorly reconstructed p_T^{miss} . Specifically, the filters select events with a well-reconstructed primary vertex, veto events with misreconstructed muons, veto events with noise and/or bad calibration in the calorimeters, and veto events affected by beam halo. These filters have been found to have a negligible effect on signal acceptance.

Standard identification (ID) and selection criteria, following central CMS guidelines, are applied to each object type. These criteria are summarized in Tables 6.1, 6.2, 6.3, 6.4, and 6.5, covering primary vertices, jets, electrons, muons, and hadronic taus. In cases requiring the selection of a single primary vertex, the vertex with the highest scalar sum of physics-object p_T^2 is chosen as the primary pp interaction vertex. The physics objects contributing to this sum are defined by the output of a jet clustering algorithm [232, 233, 236] applied to all charged tracks associated with the vertex, along with the corresponding missing transverse momentum. The transverse and longitudinal impact parameters of a track relative to this vertex are given by

$$d_{xy} \equiv \frac{-(v_x - x)p_y + (v_y - y)p_x}{p_T} \quad \text{and} \quad d_z \equiv (v_z - z) - \frac{(v_x - x)p_x + (v_y - y)p_y}{p_T} \cdot \frac{p_z}{p_T}, \quad (6.1)$$

where (v_x, v_y, v_z) denotes the point of closest approach of the track to the CMS detector origin, and (x, y, z) represents the position of the primary vertex. d_{xy} will also be referred to as d_0 throughout the work.

Table 6.1: Requirements used to select primary vertices in the 2022 and 2023 data sets. The criteria take into account the validity of the primary vertex (based on some minimum thresholds), the number of degrees of freedom fitted and its position in the z axis and the $x - y$ plane, respectively.

selection name	variable	selection
good primary vertex	isValid	= true
	ndof	≥ 4
	$ z $	$< 24 \text{ cm}$
	ρ	$< 2 \text{ cm}$

The primary objects used to reconstruct signal candidates are charged particle tracks. Using the CMSSW namings, the collection referred to as “isolatedTracks”

Table 6.2: ID criteria for tight jets with lepton veto defined for both 2022 and 2023. The criteria take into account the neutral and charged, hadronic and electromagnetic energy fractions (measured at HCAL and ECAL, respectively), the total and charged number of constituents, and the amount of energy coming from muons, respectively. More details on the determination of the ID requirements can be found in [237].

variable	requirement
neutral hadron fraction	< 0.99
charged hadron fraction	> 0.01
neutral EM fraction	< 0.9
charged EM fraction	< 0.8
number of constituents	> 1
charged multiplicity	> 0
muon fraction	< 0.8

in MiniAOD is employed, comprising `IsolatedTrack` objects formed from a union of PF candidates, `lostTracks`, and `generalTracks`, with a dedicated procedure for duplicate removal. The collection includes tracks if they have $p_T > 20$ GeV, or if they have $p_T > 5$ GeV while passing a minimal isolation requirement. Given that a $p_T > 50$ GeV requirement is later imposed during track selection (see Section 6.2.2), this collection is sufficient. Importantly, these tracks provide access the tracks’ hit pattern.

As described in Section 4.2, calorimeter jets are also used in this analysis, although indirectly, through their association with `isolatedTracks`. The jets in question are the “ak4CaloJets” from AOD, constructed as `CaloJets` with $\Delta R = 0.4$ using calorimetric tower inputs. The inputs to the ak4CaloJets have a minimum transverse energy E_T , i.e., $E \cos(\theta)$, of 0.3 GeV, and jets are required to have $p_T > 10$ GeV. No energy corrections are applied to these jets. They serve as the basis for the `matchedCaloJetEmEnergy` and `matchedCaloJetHadEnergy` variables, which act as proxies for the local calorimeter energy close to isolated tracks.

6.2 Event and Track Selection

To refine the signal region sample, an offline event selection is required on top of the online HLT selection described in Section 4.3. In this search, this selection is divided into four steps that are applied sequentially: the basic selection, the

Table 6.3: Requirements for selecting tight and loose electrons. The values outside (inside) parenthesis are used when $|\eta_{\text{supercluster}}| < 1.479$ ($|\eta_{\text{supercluster}}| > 1.479$), where a supercluster (SC) is a collection of clusters, i.e., regions with measured energy that exceed the ECAL crystals' background noise. These requirements were used for both the 2022 and 2023 event data sets. The criteria take into account the SC crystals' energy distribution in η and ϕ , the fraction of the sum of HCAL energy centered around the SC and the SC's energy, the PU-corrected relative isolation, the difference between the inverse of the SC energy and the track momentum, the transverse and longitudinal impact parameters, the amount of missing inner hits and if a photon has been converted to an electron, respectively. A more detailed description of the reconstruction and identification of electrons can be found in [238].

variable	requirement	
	tight ID	loose ID
full $5 \times 5 \sigma_{i\eta i\eta}$	$< 0.0101(0.027)$	$< 0.0107(0.0275)$
$ \Delta\eta_{\text{seed}} $	$< 0.00411(0.00938)$	$< 0.00691(0.0121)$
$ \Delta\phi_{\text{in}} $	$< 0.116(0.164)$	$< 0.175(0.228)$
H/E	$< 0.02(0.02)$	$< 0.05(0.05)$
	$+1.16(0.5)/E_{\text{SC}} +$	$+1.28(2.3)/E_{\text{SC}} +$
	$+0.0422(0.262) * \rho/E_{\text{SC}} +$	$+0.0422(0.262) * \rho/E_{\text{SC}}$
rel. iso. with ρ -corr.	$< 0.0388(0.0544)$	$< 0.194(0.184)$
	$+0.535(0.519)/p_{\text{T}}$	$+0.535(0.519)/p_{\text{T}}$
$ 1/E - 1/p $	$< 0.023(0.018)$	$< 0.138(0.127)$
$ d_{xy} $	$< 0.05(0.10) \text{ cm}$	$< 0.05(0.10) \text{ cm}$
$ d_z $	$< 0.10(0.20) \text{ cm}$	$< 0.10(0.20) \text{ cm}$
missing inner hits	≤ 1	≤ 1
has matched conversion	$= \text{true}$	$= \text{true}$

Table 6.4: Criteria for identifying tight and loose muons in the 2022 and 2023 data sets. The criteria take into account if the muon is a global muon based on a minimal set of thresholds, if it was reconstructed by the PF algorithm, its normalized χ^2 , the number of valid hits and matched stations in the muon chamber, its transverse and longitudinal impact parameters, the amount of valid hits in the pixel tracker and in the full tracker, and the relative isolation, respectively. A more detailed description about the reconstruction and identification of muons can be found in [239, 240].

variable	requirement	
	tight ID	loose ID
isGlobalMuon	= true	= true
isPFMuon	= true	= true
χ^2/ndof	< 10	
valid muon hits	> 0	
matched muon stations	> 1	
$ d_{xy} $	< 0.2 cm	
$ d_z $	< 0.5 cm	
valid pixel hits	> 0	
tracker layers with hits	≥ 10	
rel. iso. with $\Delta\beta$ -corr.	< 0.15	

Table 6.5: Hadronic tau ID with light flavor rejection using tau ID sources defined for the 2022 and 2023 data sets. The criteria take into account the reconstructed decay modes of the tau, its isolation, and the discrimination between taus and electrons and muons, respectively. More details on the reconstruction and identification of hadronic taus can be found in [241, 242].

selection name	variable	requirement
hadronic tau ID	decayModeFindingNewDMs	> 0.5
	byTightCombinedIsolationDeltaBetaCorr3Hits	> 0.5
	byVVVLooseDeepTau2018v2p5VSe	> 0.5
	byVLooseDeepTau2018v2p5VSmu	> 0.5

isolated track selection, the candidate track selection, and the disappearing track selection. Each set of requirements refines the events to extract those consistent with a disappearing track signature.

6.2.1 Basic Selection

The first step is called the basic selection, which selects events that have high p_T^{miss} recoiling against a high p_T jet. The criteria are listed in Table 6.6. Although the $p_T^{\text{miss, no } \mu} > 120 \text{ GeV}$ requirement is below the point where the HLT selection reaches 100% efficiency, as shown in Figure 4.12, it is used to increase the number of possible signal events that can be selected. The angular requirements are needed to reduce the very large background from SM events composed uniquely of jets produced through the strong interaction, referred to as QCD background. The criterion $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})| > 0.5$ is used to avoid events with badly measured jet energy, while $\max |\Delta\phi_{\text{jet, jet}}| < 2.5$ is used to veto dijet events. Figure 6.2 shows the distribution of those variables in data and MC.

Table 6.6: Criteria defining the basic selection. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
		event passes p_T^{miss} triggers
≥ 1	primary vertices	passing good primary vertex requirements
	$p_T^{\text{miss, no } \mu}$	$p_T > 120 \text{ GeV}$
≥ 1	jets	$p_T > 110 \text{ GeV}$
≥ 1	jets	$ \eta < 2.4$
≥ 1	jets	passing tight ID with lepton veto requirements
	jet pairs (if any)	$\max \Delta\phi_{\text{jet, jet}} < 2.5$
	$p_T^{\text{miss, no } \mu}$	$ \Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu}) > 0.5$

6.2.2 Isolated track selection

Following the basic selection, the events are required to have a high p_T isolated track that is continuous (has no missing inner or middle hits) and does not fall into regions of known inefficiency in the CMS detector. The isolated track selection requirements are listed in Table 6.7. The $p_T > 55 \text{ GeV}$ requirement is chosen to match the region where the $p_T^{\text{miss}} + \text{IsoTrk}$ HLT paths reach peak efficiency, while

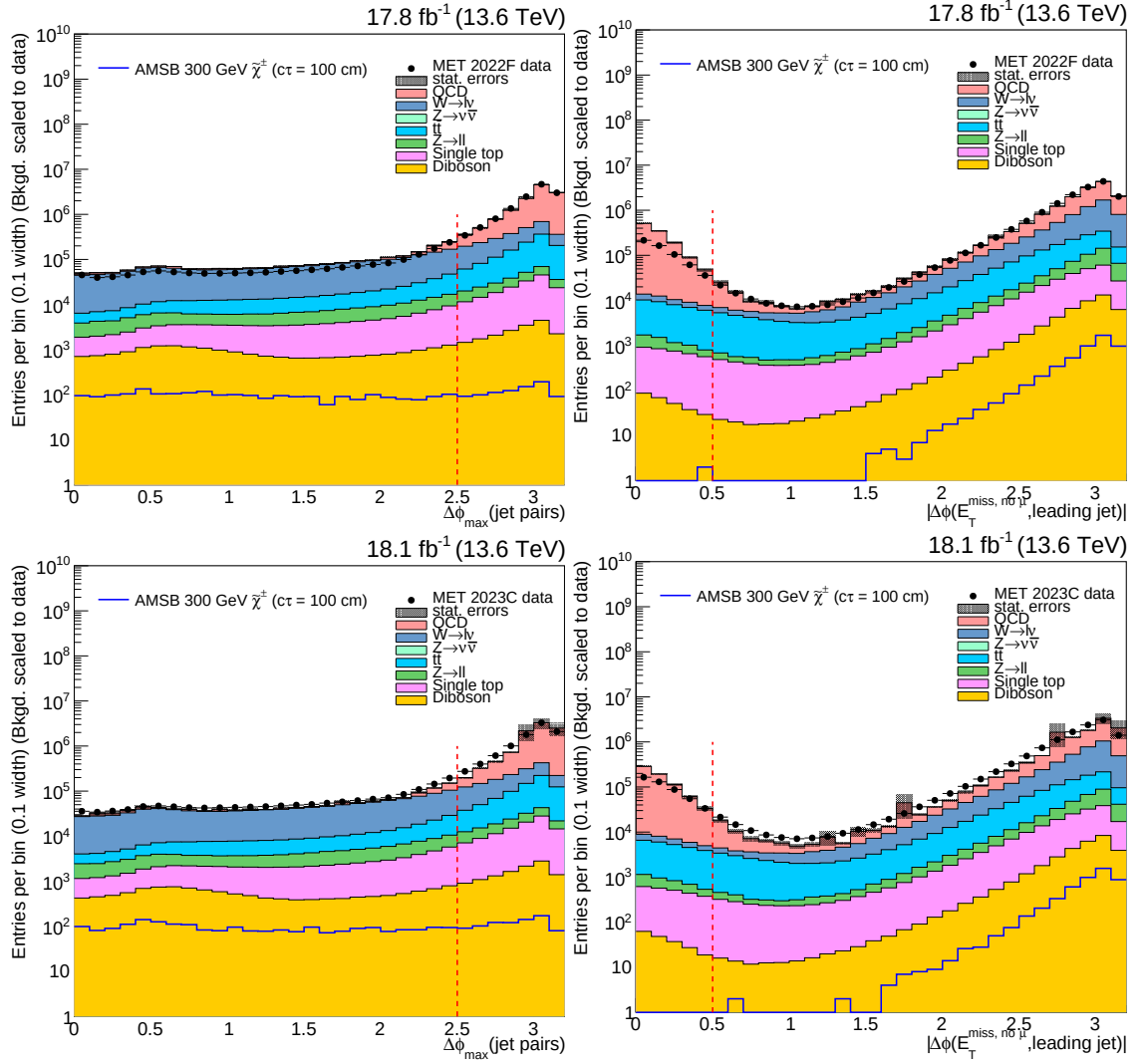


Figure 6.2: Distributions of $\max |\Delta\phi_{\text{jet,jet}}|$ (left) and $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})|$ (right) for events in the basic selection, without angular requirements applied. On the top are displayed 2022 events, and on the bottom are 2023 events. Red dashed lines indicate the set threshold of the criteria.

the $|\eta| < 2.1$ targets the region where tracks are almost guaranteed to traverse at least four layers of the pixel detector. The amount of valid and missing inner and middle hits guarantees that the selected track is of high quality. The PF-based isolation is calculated as the scalar sum of the p_T of the charged PF candidates within a cone of $\Delta R < 0.3$ relative to the candidate track in question. The value of the isolation requirement is chosen to match the selection made in `HLT_MET105_IsoTrk50_v*`. This calculation only takes into account charged PF objects that come from the primary vertex as well, i.e., their longitudinal impact parameter $|d_z|$ has to be smaller than 0.1 cm with respect to the primary vertex. This procedure mitigates the pileup dependence in the calculation. The impact parameter criteria ensure that the charged particle track is produced promptly and is consistent with the most interesting collision. Finally, tracks are required not to be inside a PF jet to guarantee their isolation.

In 2023D there was a problem with the pixel barrel, in which layers 3 and 4 (BPix3 and BPix4) of the pixel barrel detector had readout issues which implied in the loss of several modules, decreasing the efficiency of tracks reconstruction in the region of $-1.5 < \eta < -0.2$ and $-1.1 < \phi < -0.9$, as can be seen in Figure 6.3. Given that recovering those modules means that the electronics of the service cylinder would need to be replaced, a recovery was not considered. The measured inefficiency of track reconstruction in that region is of the order of 2%, which is included as a systematic uncertainty source in this search, as described in Section 6.5.2.

The fiducial selections shown in the table refer to regions of known inefficiency for reconstructing physics objects in the CMS detector. First, there are three regions in $|\eta|$ which are vetoed :

- $0.15 < |\eta| < 0.35$: there is a gap here between wheels 0 and 1 of the DT stations, where muons could be misreconstructed due to missing information and mimic a disappearing track;
- $1.42 < |\eta| < 1.65$: this is the region where the barrel and endcap sections of the ECAL overlap, where electrons and charged hadrons could be misreconstructed, producing the signal of a high- p_T isolated track with a small amount of E_{calo} ;
- $1.55 < |\eta| < 1.85$: this is the transition region between the outermost rings and innermost ring of the CSCs, implying the same as the first region

Table 6.7: Criteria defining the isolated track selection. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
event passes basic selection		
≥ 1	tracks	$p_T > 55 \text{ GeV}$
≥ 1	tracks	$ \eta < 2.1$
≥ 1	tracks	passing fiducial selections
≥ 1	tracks	number of pixel hits ≥ 4
≥ 1	tracks	missing inner hits = 0
≥ 1	tracks	missing middle hits = 0
≥ 1	tracks	rel. PF-based iso. < 0.05
≥ 1	tracks	$ d_{xy} < 0.02 \text{ cm}$ (w.r.t. primary vertex)
≥ 1	tracks	$ d_z < 0.5 \text{ cm}$ (w.r.t. primary vertex)
≥ 1	track-jet pairs	$\Delta R_{\text{track,jet}} > 0.5$

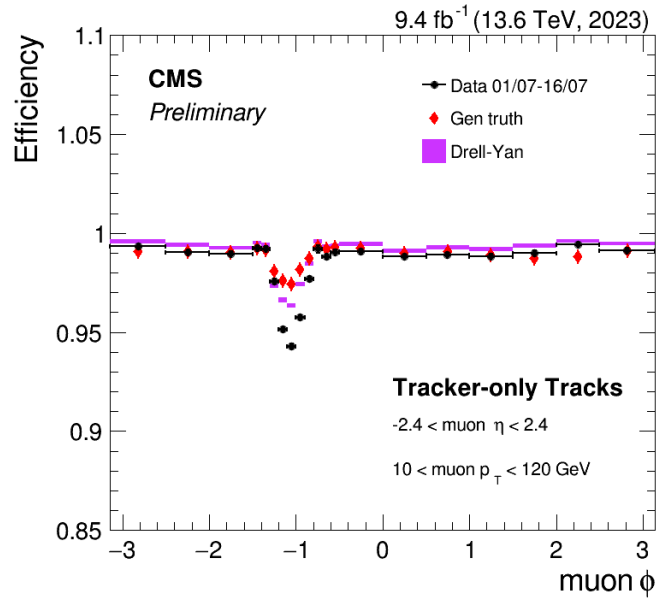


Figure 6.3: Tracking efficiency measured with a muon tag-and-probe study by the dedicated CMS group. The comparison between collected and simulated data is performed as a function of muon ϕ . Shown are comparisons with data from 2023BPix. Source: [243].

mentioned above

as can be seen in Figure 3.5. More explicitly, Figure 6.4 shows the tracking efficiency as a function of η in events of $Z \rightarrow \mu\mu$ (left) and $Z \rightarrow ee$ (right) processes, respectively, where it is possible to see the decrease in efficiency due to the regions above.

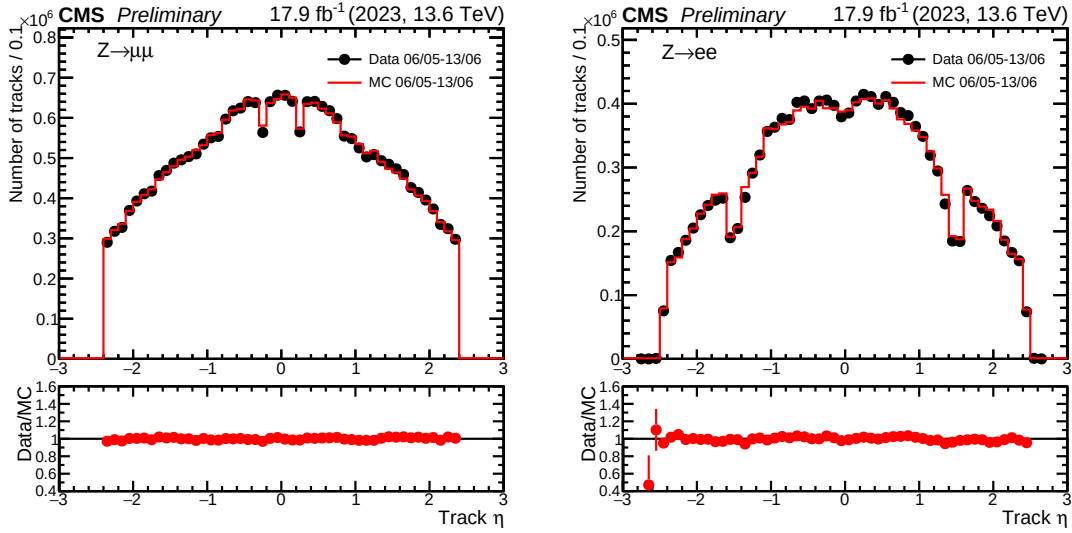


Figure 6.4: Tracking efficiency measured with $Z \rightarrow \mu\mu$ (left) and $Z \rightarrow ee$ (right) tracks, performed by the dedicated CMS group. The efficiency is measured as a function of η , where it is possible to note the lower efficiency regions that are vetoed in this search. Source: [244].

Additionally, at the very center of the TOB region of the strip tracker, a track with $\eta = 0$ that originates close to $z = 0$ would only traverse the edges of the TOB modules, as can be seen in Figure 6.5, making it possible for the track to have a large amount of $N_{\text{miss}}^{\text{outer hits}}$. In the 2015–2016 search, two tracks with those characteristics were observed. To avoid this region, tracks are vetoed if $|d_z^{\text{w.r.t. origin}}| < 0.5$ cm and $|\lambda| < 10^{-3}$, where $\lambda = \frac{\pi}{2} - \theta$, where θ is the angle of the track with respect to the z axis.

Specially due to a water leak in the ECAL endcap during 2022E, F, and G eras, events with jets falling in the regions shown in Figure 6.6 are vetoed. Also, because of noisy or dead sensors in the ECAL, tracks that are within $\Delta R < 0.05$ of the regions shown in Figure 6.7 are vetoed from the events. Besides the extraordinary occurrences that happened in 2022EFG and 2023D, all the jet veto and ECAL

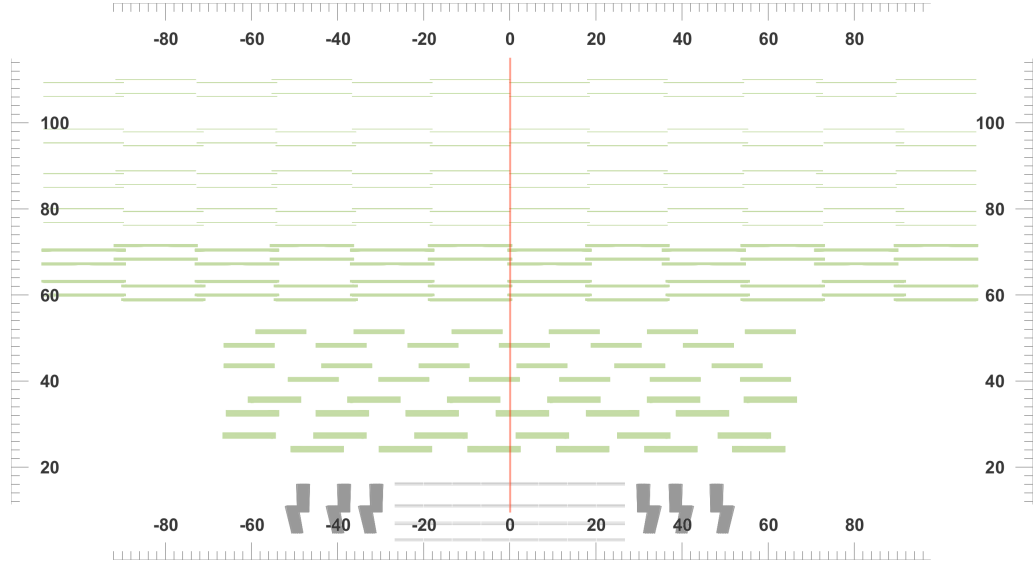


Figure 6.5: ρ - z plane schematic of the CMS silicon tracker. The red line represents a track with $\eta \simeq 0$. The silicon tracker endcaps are not shown.

noisy/dead channels maps are very similar.

Finally, lepton reconstruction inefficient regions are calculated with the so-called fiducial maps, which display the inefficient regions in $\eta \times \phi$ bins, and the event is vetoed if an isolated track falls within $\Delta R < 0.05$ of regions with 2σ above the mean inefficiency. This is needed since an isolated high- p_T lepton that is not reconstructed properly could mimic the disappearing tracks signal. These regions are calculated with the tag-and-probe method, where the tag is a well-reconstructed lepton, and the probe is a track that should be associated with a lepton but was not identified as such. To select pairs of lepton-track where the track should be associated to a lepton of the same flavor and opposite charge, they must be coming from a Z boson, and are chosen following the selections in Tables 6.8 and 6.9, to account for electrons and muons separately. To check that tracks were effectively misreconstructed, they must pass the requirement $\Delta R_{\text{track, loose lepton}} > 0.15$, which guarantees that they are not associated with any lepton. The inefficient regions are calculated as the ratio between the number of events after and before the veto. Examples of fiducial maps can be found in Figure 6.8.

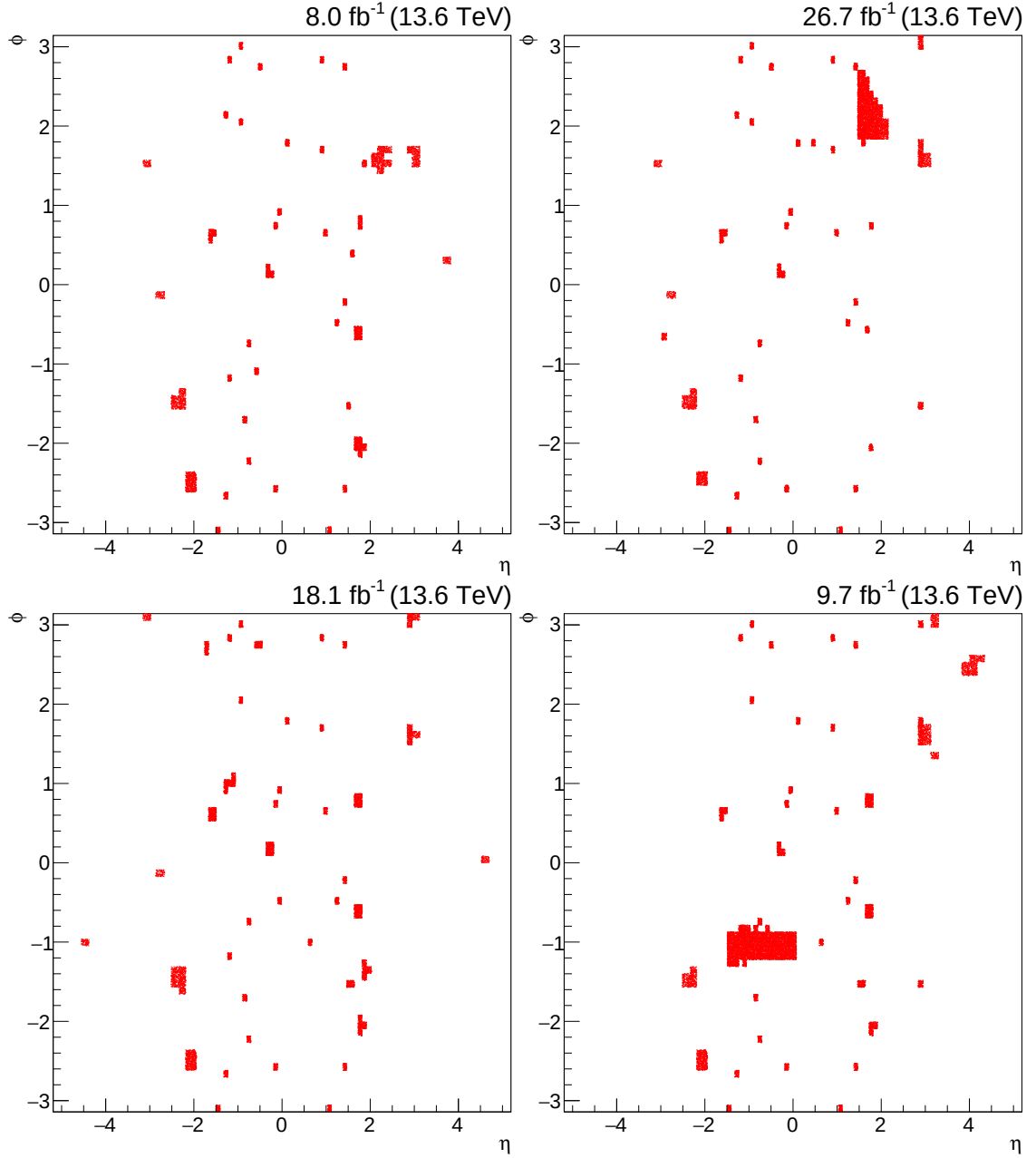


Figure 6.6: Jet veto $\eta \times \phi$ maps. Events with jets in the red regions are vetoed. Shown are periods 2022CD (top left), 2022EFG (top right), 2023C (bottom left), and 2023D (bottom right). The large veto region in the 2022EFG map at $\eta \approx 2$ is due to the water leak in the ECAL endcap, and the $\eta \approx -1$ region in the 2023D map is related to the pixel barrel issue.

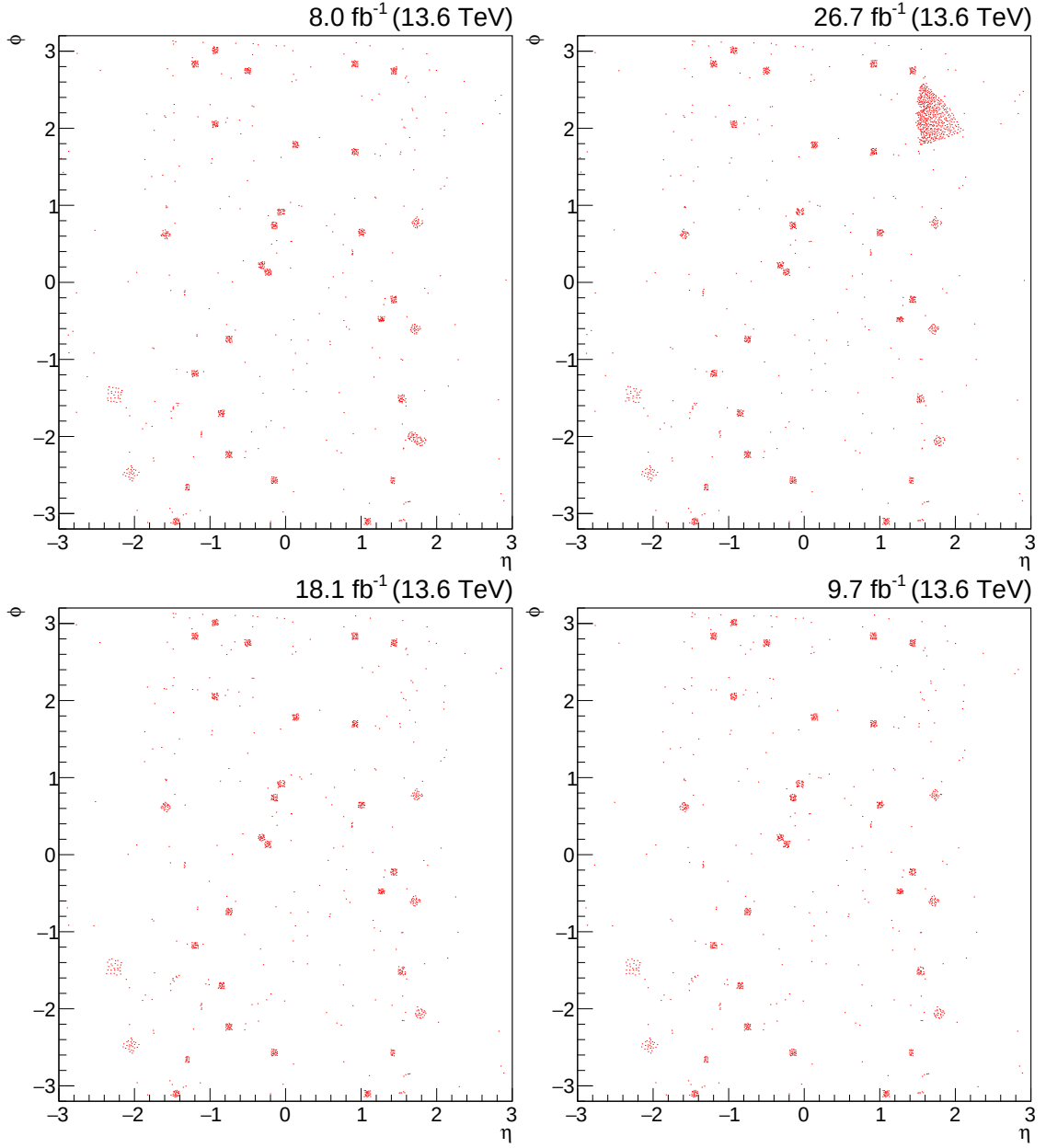


Figure 6.7: Noisy/dead ECAL channels $\eta \times \phi$ maps. This information is estimated by the relevant CMS group and is stored in each event. Shown are periods 2022CD (top left), 2022EFG (top right), 2023C (bottom left), and 2023D (bottom right). Tracks within $\Delta R < 0.05$ of any of these channels are vetoed.

Table 6.8: Tag-and-probe selection to study the reconstruction inefficiency of electrons. The criteria are applied sequentially, with only the objects passing a given selection being used in further requirements. The tag is the selected electron, and the probe is the selected track. Except for the p_T and the pair requirements of the tag-and-probe, the disappearing track selection, with the electron veto (defined in Table 6.15) removed, is applied to select probe tracks.

quantity	object	selection
	event passes SingleElectron/EGamma triggers	
≥ 1	electrons	$p_T > 32 \text{ GeV}$
≥ 1	electrons	$ \eta < 2.1$
≥ 1	electrons	passing tight electron ID
	exactly one passing electron chosen randomly	
≥ 1	tracks	$p_T > 30 \text{ GeV}$
≥ 1	tracks	$ \eta < 2.1$
≥ 1	tracks	$ \eta < 0.15 \text{ OR } \eta > 0.35$
≥ 1	tracks	$ \eta < 1.42 \text{ OR } \eta > 1.65$
≥ 1	tracks	$ \eta < 1.55 \text{ OR } \eta > 1.85$
≥ 1	tracks	$\min \Delta R_{\text{track,noisy/dead ECAL ch.}} > 0.05$
≥ 1	tracks	$ d_z > 0.5 \text{ cm OR } \lambda > 10^{-3}$
≥ 1	tracks	number of pixel hits ≥ 4
≥ 1	tracks	missing inner hits = 0
≥ 1	tracks	missing middle hits = 0
≥ 1	tracks	rel. PF-based iso. < 0.05
≥ 1	tracks	$ d_{xy} < 0.02 \text{ cm}$
≥ 1	tracks	$ d_z < 0.5 \text{ cm}$
≥ 1	track-jet pairs	$\Delta R_{\text{track,jet}} > 0.5$
≥ 1	track-electron pairs	$M_{\text{track,electron}} > 10 \text{ GeV}$
≥ 1	tracks	$\min \Delta R_{\text{track,muon}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track,had. tau}} > 0.15$
	exactly one passing track chosen randomly	
= 1	track-electron pairs	$ M_{\text{track,electron}} - M_Z < 10 \text{ GeV}$
= 1	track-electron pairs	$q_{\text{track}} \cdot q_{\text{electron}} < 0$
≥ 1	track	$n_{\text{layers}} \geq 4$ (three signal region bins)

Table 6.9: Tag-and-probe selection to study the reconstruction inefficiency of muons. The criteria are applied sequentially, with only the objects passing a given selection being used in further requirements. The tag is the selected muon, and the probe is the selected track. Except for the p_T and the pair requirements of the tag-and-probe, the disappearing track selection, with the muon veto (defined in Table 6.15) removed, is applied to select probe tracks.

quantity	object	selection
event passes SingleMuon triggers		
≥ 1	muons	$p_T > 26 \text{ GeV}$
≥ 1	muons	$ \eta < 2.1$
≥ 1	muons	passing tight muon ID
	exactly one passing muon chosen randomly	
≥ 1	tracks	$p_T > 30 \text{ GeV}$
≥ 1	tracks	$ \eta < 2.1$
≥ 1	tracks	$ \eta < 0.15 \text{ OR } \eta > 0.35$
≥ 1	tracks	$ \eta < 1.42 \text{ OR } \eta > 1.65$
≥ 1	tracks	$ \eta < 1.55 \text{ OR } \eta > 1.85$
≥ 1	tracks	$\min \Delta R_{\text{track,noisy/dead ECAL ch.}} > 0.05$
≥ 1	tracks	$ d_z > 0.5 \text{ cm OR } \lambda > 10^{-3}$
≥ 1	tracks	number of pixel hits ≥ 4
≥ 1	tracks	missing inner hits = 0
≥ 1	tracks	missing middle hits = 0
≥ 1	tracks	rel. PF-based iso. < 0.05
≥ 1	tracks	$ d_{xy} < 0.02 \text{ cm}$
≥ 1	tracks	$ d_z < 0.5 \text{ cm}$
≥ 1	track-jet pairs	$\Delta R_{\text{track,jet}} > 0.5$
≥ 1	track-muon pairs	$M_{\text{track,muon}} > 10 \text{ GeV}$
≥ 1	tracks	$\min \Delta R_{\text{track,electron}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track,had. tau}} > 0.15$
≥ 1	tracks	$E_{\text{calo}} < 10 \text{ GeV}$
	exactly one passing track chosen randomly	
= 1	track-muon pairs	$ M_{\text{track,muon}} - M_Z < 10 \text{ GeV}$
= 1	track-muon pairs	$q_{\text{track}} \cdot q_{\text{muon}} < 0$
≥ 1	track	$n_{\text{layers}} \geq 4$ (three signal region bins)

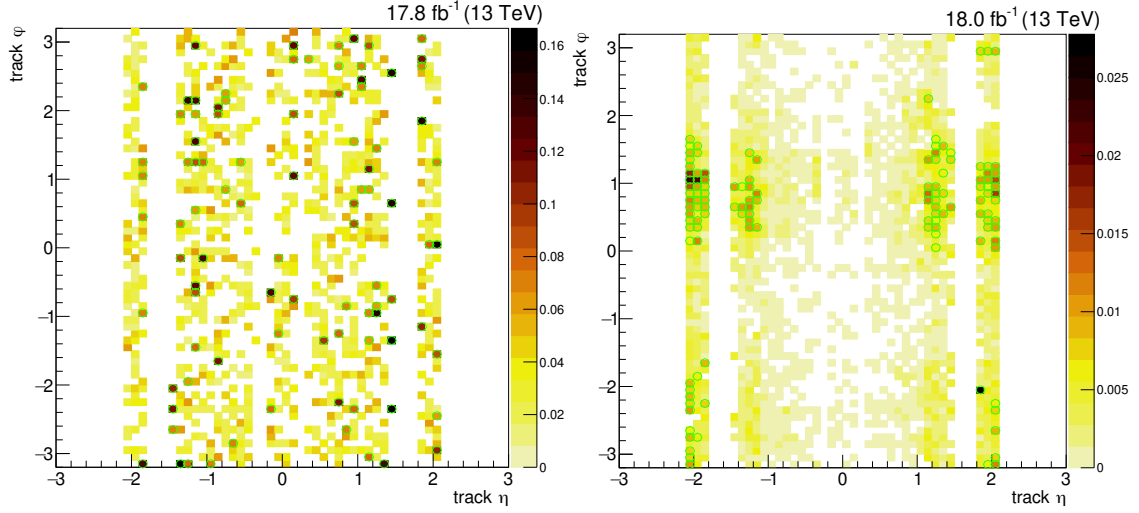


Figure 6.8: Tag-and-probe measured lepton reconstruction inefficiencies. Electrons (left) and muons (right) are estimated separately for each era of the Run 3 data collection. Shown is 2022F. Bins with inefficiency higher than $2\sigma_{\text{mean}}$ above the average inefficiency are used to veto tracks, which are marked with green circles in each image. Both maps are used in the respective era selection to account for all flavors of inefficiently reconstructed leptons.

6.2.3 Candidate track selection

The next selection selects events in which the isolated track is not associated with any reconstructed lepton, that is, the geometric distance between an isolated track with reconstructed leptons should be large, as displayed in Table 6.10. This is essential to remove isolated leptons that come from the decay of SM gauge bosons, since the isolated track selection does not generally reject those. All electrons and muons available in the MiniAOD are used, while hadronic taus have to pass through the pre-selection recommended centrally by CMS, shown in Table 6.5. The threshold set ensures that almost all events with reconstructed leptons will be vetoed.

6.2.4 Disappearing track selection

Finally, to effectively select on disappearing tracks and discriminate between signal and BG, two variables are used: the calorimeter energy associated with a candidate track and the number of missing outer hits of the selected track, both defined in Chapter 4. Table 6.11 shows the requirements on those variables. Events that pass the disappearing tracks selection comprise the signal region events. The

Table 6.10: Criteria defining the candidate track selection. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements. All available electrons and muons in MiniAOD are used during this matching to reject as many leptons as possible. Hadronic taus are identified using the requirements listed above in table 6.5 with the isolation selection removed.

quantity	object	selection
event passes isolated track selection		
≥ 1	tracks	$\min \Delta R_{\text{track,electron}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track,muon}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track,had. tau}} > 0.15$

signal region is further divided into three bins of 4, 5, and 6 or more (6+) tracker layers with a valid measurement of the selected tracks, to increase the sensitivity of the search for smaller $c\tau$. The comparison on the number of events passing the full disappearing tracks selection with an estimation of the expected amount of events coming from BG is what the cut and count method uses to perform a hypothesis test; the null hypothesis is SM only, with the alternative hypothesis being SM+AMSB.

When comparing signal and SM MC events that went through the full disappearing track selection except for the variable being plotted, it is possible to see a very good separation between both samples, as shown in Figures 6.9 and 6.10.

Table 6.11: Criteria defining the disappearing track selection. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
event passes candidate track selection		
≥ 1	tracks	$E_{\text{calo}} < 10 \text{ GeV}$
≥ 1	tracks	missing outer hits ≥ 3

Figures 6.11, 6.12 and 6.13 show the cut flows for signal events with varied masses and lifetimes. It is possible to notice some interesting points on the behavior of the requirements' efficiency: for the lower lifetime, the track require-

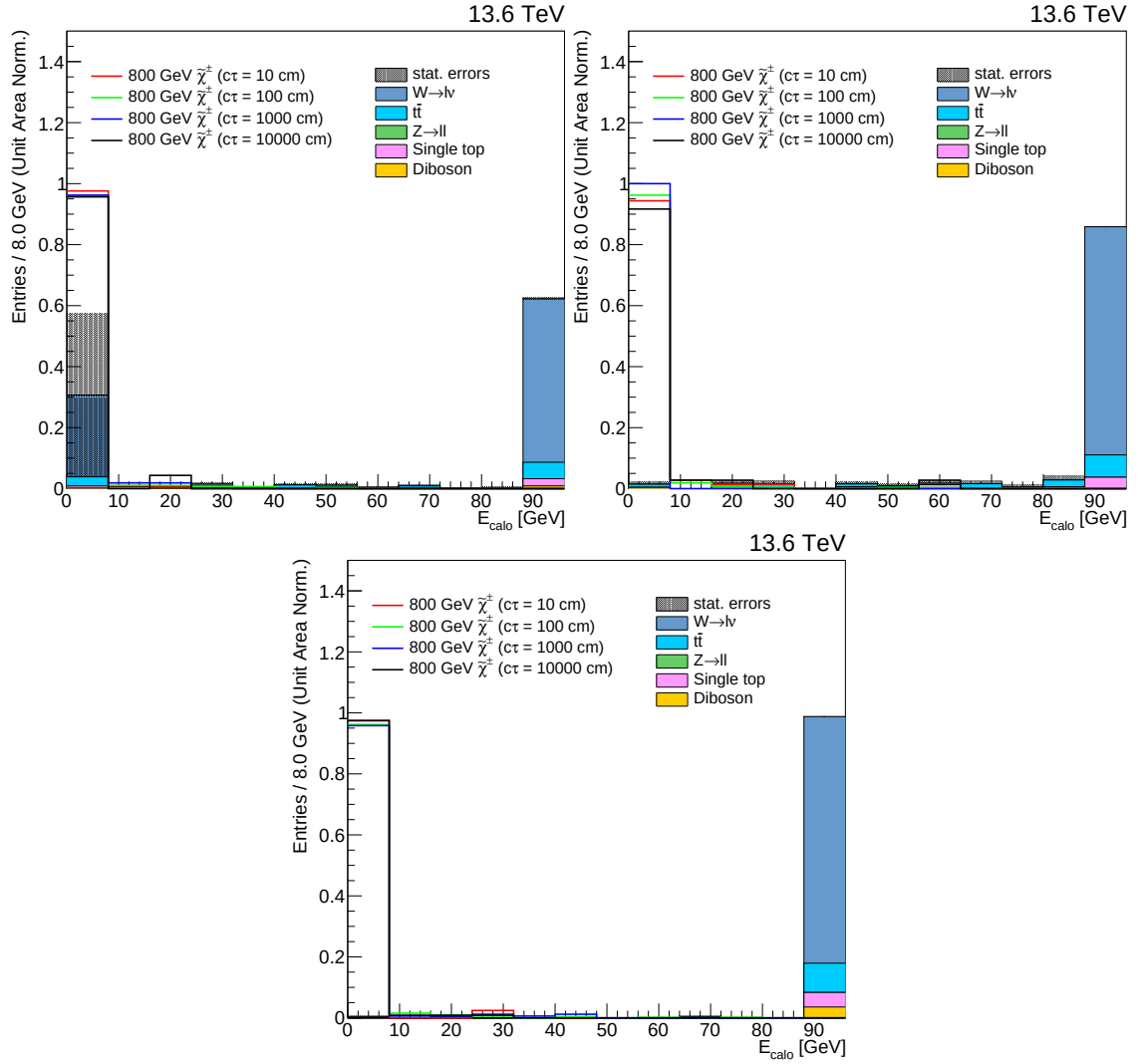


Figure 6.9: Tracks E_{calo} distributions. Shown are events from SM and signal MC simulations that passed the disappearing tracks selection without the criterion on the variable under study. Each signal region bin is being plotted: $n_{\text{layers}} = 4$ (top left), 5 (top right), ≥ 6 (bottom). 2022 samples were used to produce the images.

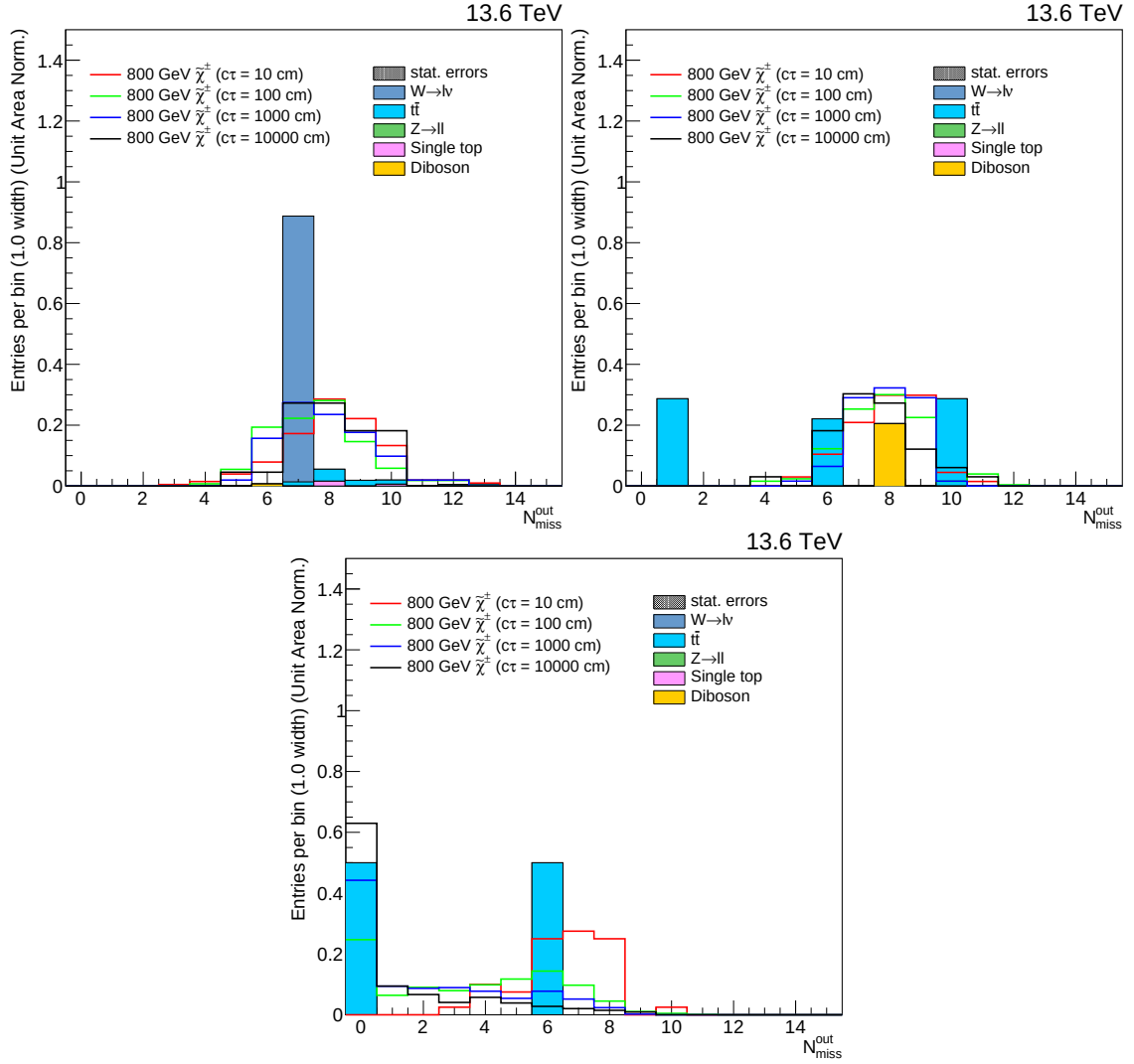


Figure 6.10: Tracks $N_{\text{miss}}^{\text{outer hits}}$ distributions. Shown are events from SM and signal MC simulations that passed the disappearing tracks selection without the criterion on the variable under study. Each signal region bin is being plotted: $n_{\text{layers}} = 4$ (top left), 5 (top right), ≥ 6 (bottom). 2022 samples were used to produce the images.

ments decrease the efficiency substantially, given that shorter chargino tracks are more unlikely to be reconstructed; while for the longer lifetime, the criterion $\min \Delta R_{\text{track, muon}} > 0.15$ exhibits a large drop in efficiency, given that longer chargino tracks are more likely to get to the muon chambers and be identified as muons. Also, in the latter case, the longer tracks would have small $N_{\text{miss}}^{\text{outer hits}}$. For completeness, Figure 6.14 show the efficiencies for the complete disappearing tracks selection applied over the full mass/lifetime space using wino-like charginos, for the three n_{layers} categories. Even though the difference is subtle, it is possible to notice that the region with higher efficiencies, concentrated at higher chargino masses, changes for higher lifetimes with increasing n_{layers} .

6.3 Background Estimation

In this analysis, the background estimation is completely data-driven and depends on modeling the detector misreconstructions, since no particle in the standard model can mimic a disappearing track. There are two main sources: non-identified charged leptons and spurious tracks.

6.3.1 Charged Leptons

High- p_T isolated leptons can be misidentified as such and leave only an isolated track signal. If its energy deposit in the calorimeters is also small and it misses outer hits, it is a perfect match to the disappearing track signature. To estimate this possibility, equation 6.2 is used:

$$N_{\text{est}}^l = \frac{N_{\text{ctrl}}^l}{\epsilon_{\text{trigger}}^l} P_{\text{veto}} P_{\text{offline}} P_{\text{trigger}}, \quad (6.2)$$

where N_{ctrl}^l is the amount of events passing the single lepton control region selections defined below, $\epsilon_{\text{trigger}}^l$ is used to correct the efficiency of the single lepton triggers used to estimate N_{ctrl}^l , P_{veto} is the probability for the leptons not to be identified as leptons, P_{offline} is the probability for the events with non-identified leptons to pass the basic selection offline p_T^{miss} requirement and P_{trigger} is the probability for these events to pass the signal HLT paths.

Each lepton flavor selection for the control regions can be found in Tables 6.12, 6.13, and 6.14. The requirements select events with an isolated single lepton, an

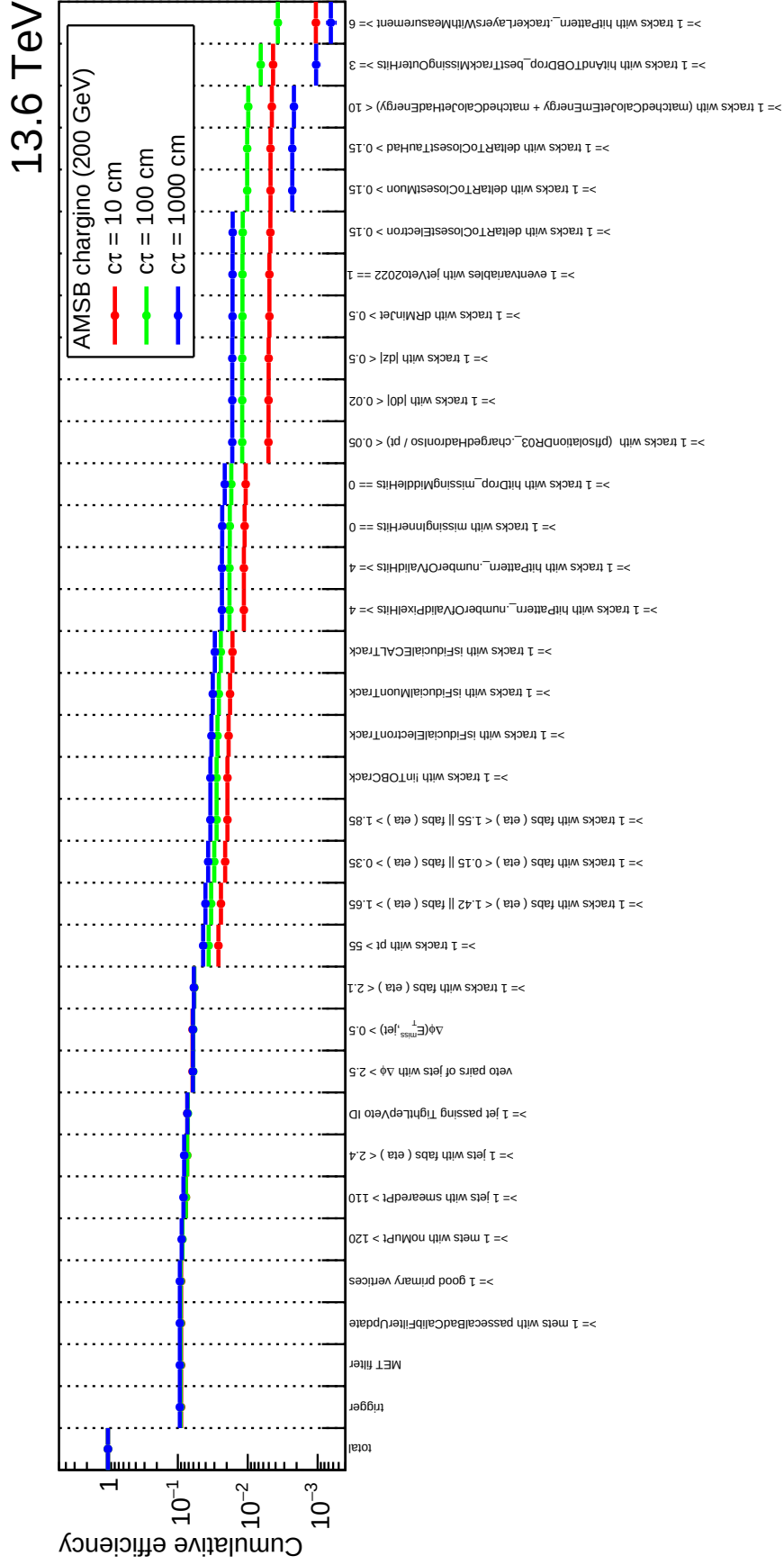


Figure 6.11: Disappearing track selection cut flow of three AMSB signal points: 10, 100, and 1000 cm of $c\tau$ for wino-like charginos with $m_{\tilde{\chi}_1^\pm} = 200$ GeV. The 2022EE samples were used to produce the image.

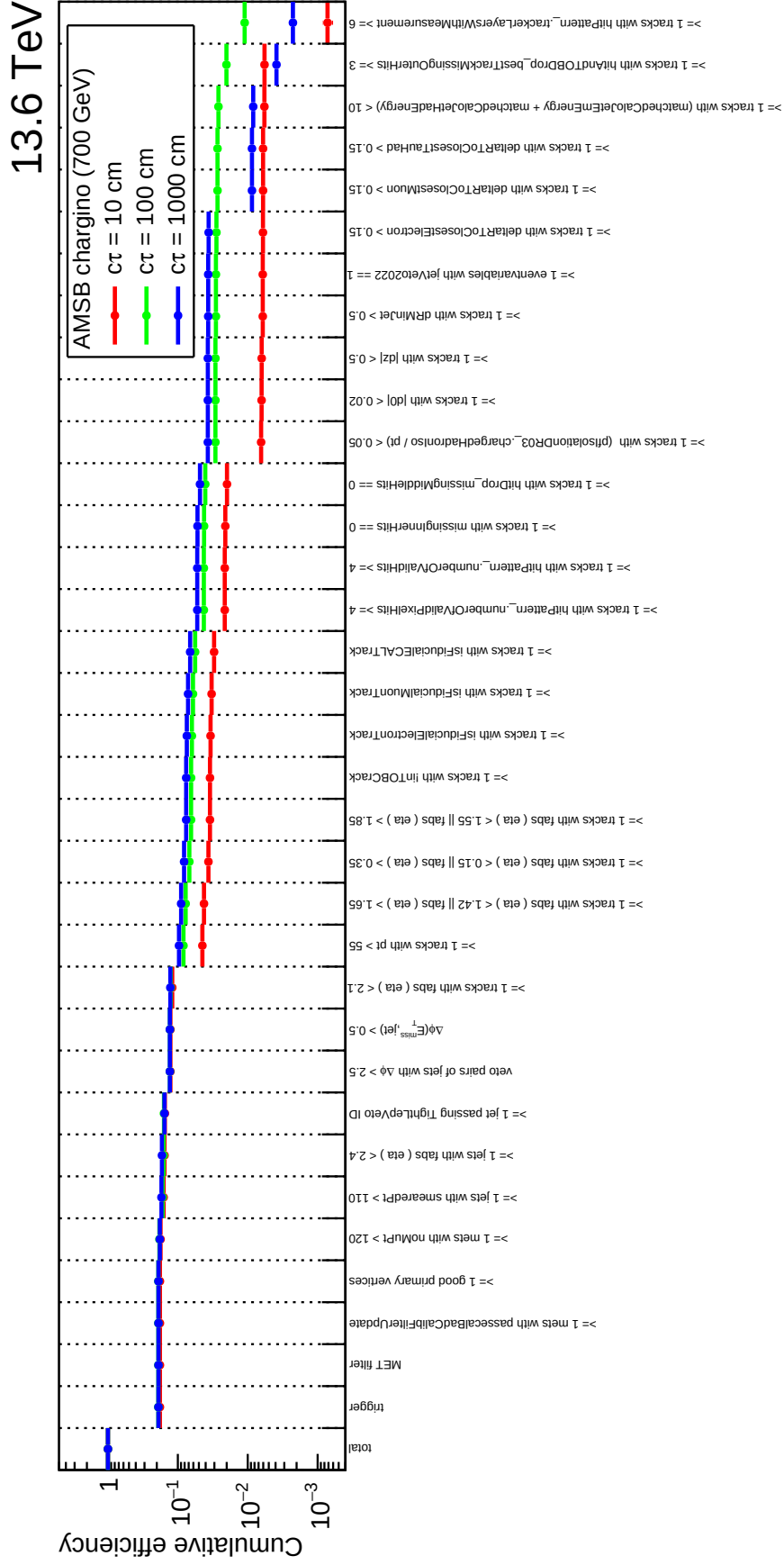


Figure 6.12: Disappearing track selection cut flow of three AMSB signal points: 10, 100, and 1000 cm of $c\tau$ for wino-like charginos with $m_{\tilde{\chi}_1^\pm} = 700$ GeV. The 2022EE samples were used to produce the image.

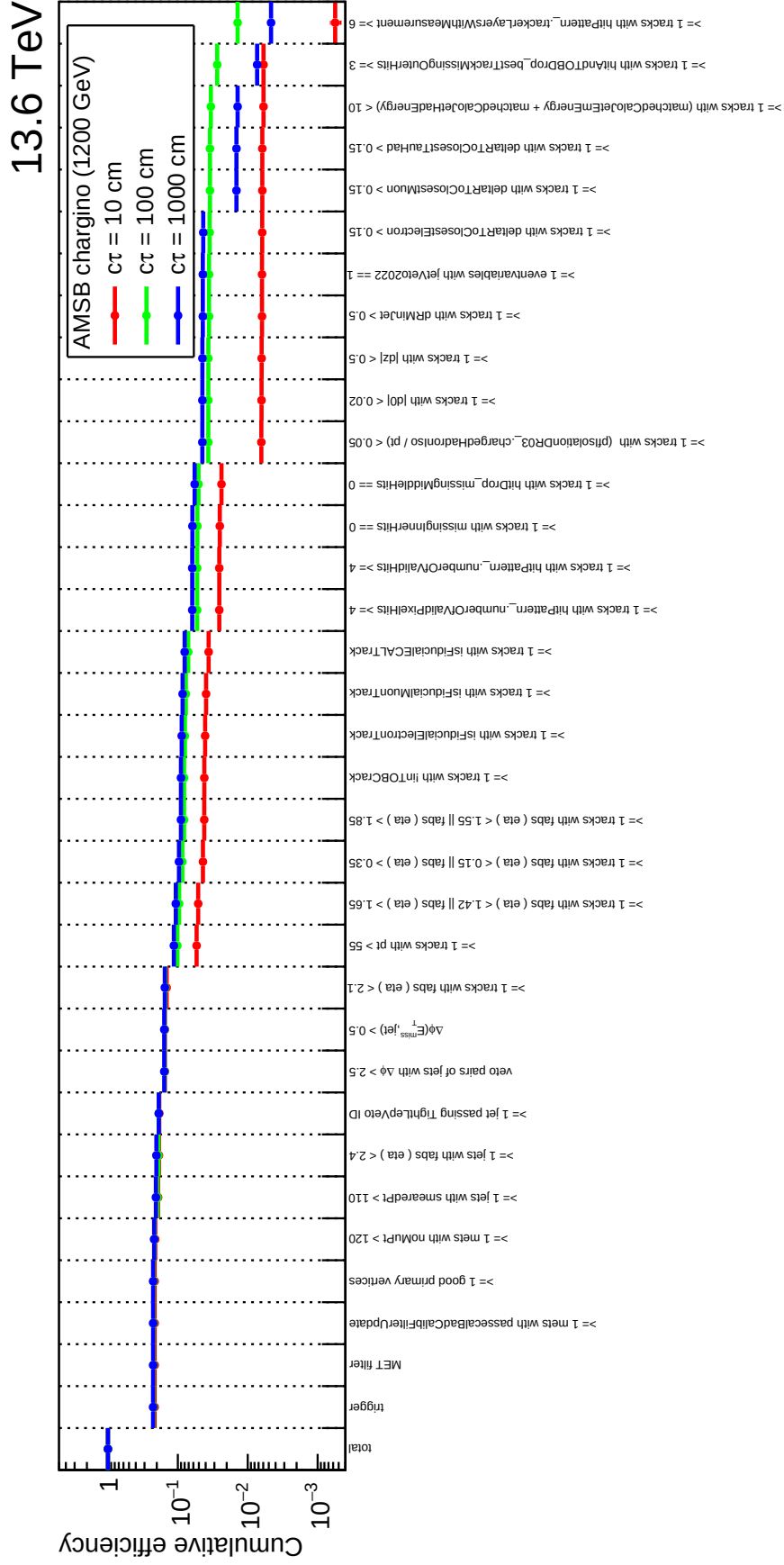


Figure 6.13: Disappearing track selection cut flow of three AMSB signal points: 10, 100, and 1000 cm of $c\tau$ for wino-like charginos with $m_{\tilde{\chi}_1^\pm} = 1200$ GeV. The 2022EE samples were used to produce the image.

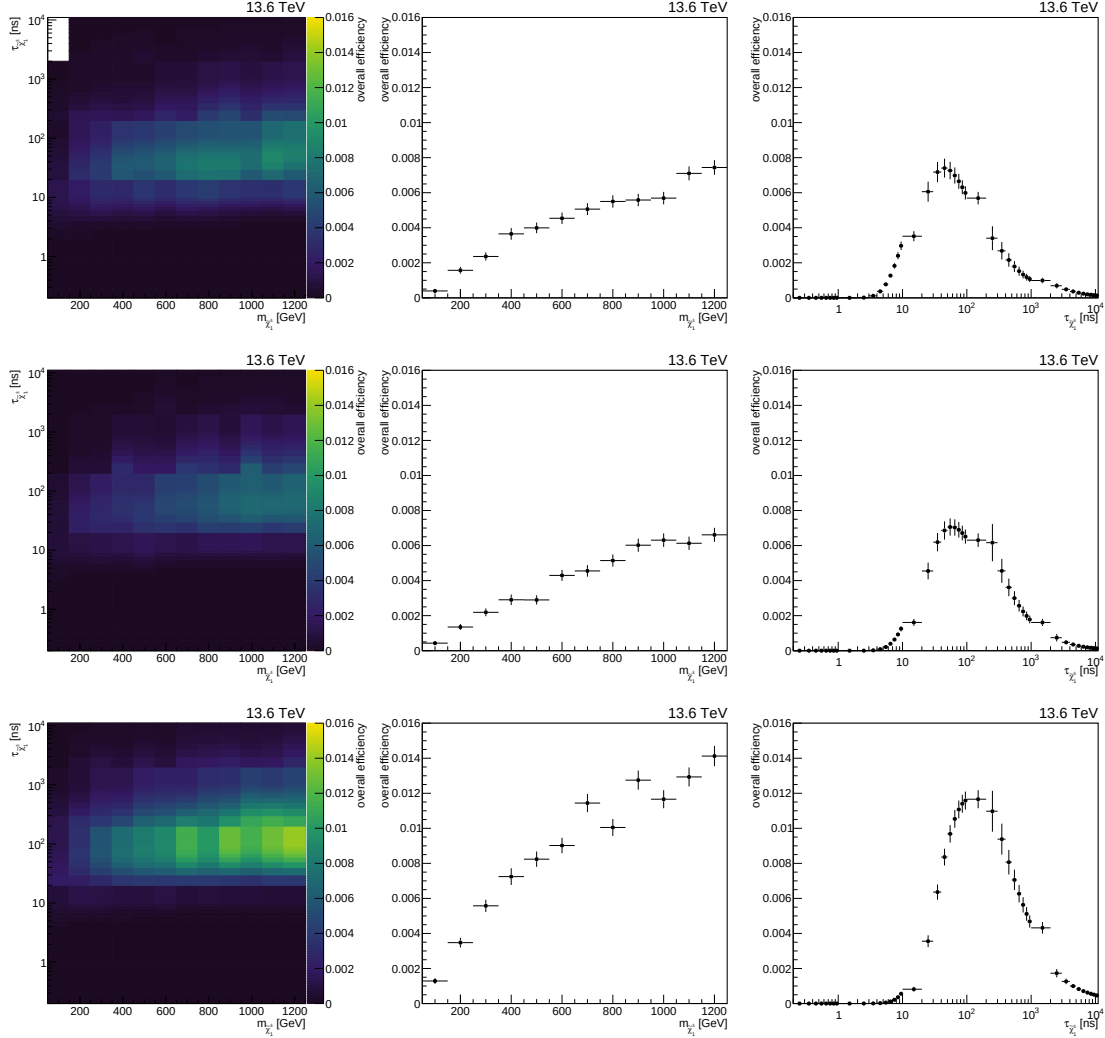


Figure 6.14: Overall efficiency of the full disappearing tracks selection as a function of chargino mass and lifetime (left column), and the overall efficiencies for $c\tau = 100$ cm (middle column) and $m_{\tilde{\chi}_1^\pm} = 1000$ GeV (right column), as a function of the remaining variable. Shown are the $n_{\text{layers}} = 4$ (top row), $n_{\text{layers}} = 5$ (middle row) and $n_{\text{layers}} = 6$ (bottom row) categories. The $m_{\tilde{\chi}_1^\pm} = 100$ GeV, $c\tau = 10000$ cm sample had 0 yield in the $n_{\text{layers}} = 4$ category, and the top left corner of the top left image had no entries. 2022EE samples were used to produce the images.

isolated track, and a high p_T hadronic jet. Because of the search region binning, this is performed for the 4, 5, and 6 or more tracker layers with measurement of the selected track.

Table 6.12: Criteria defining the single-electron control sample. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
		event passes SingleElectron/EGamma triggers
≥ 1	electrons	$p_T > 32 \text{ GeV}$
≥ 1	electrons	$ \eta < 2.1$
≥ 1	electrons	passes tight electron ID
		exactly one passing electron chosen randomly
		event passes jet criteria of basic selection
		event passes track criteria of isolated track selection
		track selected in isolated track selection matched to selected electron within $\Delta R < 0.1$

Table 6.13: Criteria defining the single-muon control sample. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
		event passes SingleMuon triggers
≥ 1	muons	$p_T > 26 \text{ GeV}$
≥ 1	muons	$ \eta < 2.1$
≥ 1	muons	passes tight muon ID
		exactly one passing muon chosen randomly
		event passes jet criteria of basic selection
		event passes track criteria of isolated track selection
		track selected in isolated track selection matched to selected muon within $\Delta R < 0.1$

Probability to Pass the Lepton Veto

To calculate P_{veto} , the same tag-and-probe selection of Tables 6.8 and 6.9 is used for electrons and muons, with the change that they now use the fiducial maps for the inefficiency regions, and for taus, the tag-and-probe selections are defined in

Table 6.14: Criteria defining the single-tau control sample. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
		event passes Tau triggers
≥ 1	taus	$p_T > 50 \text{ GeV}$
≥ 1	taus	$ \eta < 2.1$
≥ 1	taus	passes hadronic tau ID
		exactly one passing tau chosen randomly
		event passes jet criteria of basic selection
		event passes track criteria of isolated track selection
		track selected in isolated track selection matched to selected tau within $\Delta R < 0.1$

Tables 6.16 and 6.17. A requirement on the transverse mass³ of the tag-and-probe objects is set to reduce the contribution of W+jets events with the W decaying leptonically. The vetoes the probe tracks are subjected to are more constraining and are defined in Table 6.15. P_{veto} is then defined as the following:

$$P_{\text{veto}} = \frac{N_{\text{T\&P}}^{\text{veto}} - N_{\text{T\&P, SS}}^{\text{veto}}}{N_{\text{T\&P}} - N_{\text{T\&P, SS}}}, \quad (6.3)$$

where the SS subscript refers to tag-and-probe pairs of the same sign electric charge. The subtraction of those events is to remove background contributions coming from events that should not add to the Z boson events. The values of the number of events used in the calculation of P_{veto} obtained for each lepton flavor in the four data-taking periods considered in this search are shown in Table 6.18.

Probability to Pass the Offline $p_T^{\text{miss, no } \mu}$ Requirement

P_{offline} is estimated from the single lepton control region events as the probability of a non-reconstructed lepton to pass the $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})| > 0.5$ and $p_T^{\text{miss, no } \mu} > 120 \text{ GeV}$ requirements. It is determined as a ratio, where the denominator is the number of events passing the respective lepton control region selection, and the numerator applies the criteria above. An extra assumption is that, if the leptons are not correctly reconstructed, they will not account for any

³The transverse mass is defined as $M_T = \sqrt{2p_T^{\text{miss}} p_T^l (1 - \cos \phi)}$, where ϕ is the angle between the lepton and the missing transverse momentum.

Table 6.15: Lepton vetoes applied over tag-and-probe samples to estimate P_{veto} .

flavor	quantity	object	selection
electron	≥ 1	tracks	$\min \Delta R_{\text{track,electron}} > 0.15$
	≥ 1	tracks	$E_{\text{calo}} < 10 \text{ GeV}$
	≥ 1	tracks	missing outer hits ≥ 3
muon	≥ 1	tracks	$\min \Delta R_{\text{track,muon}} > 0.15$
	≥ 1	tracks	missing outer hits ≥ 3
tau	≥ 1	tracks	$\min \Delta R_{\text{track, had. tau}} > 0.15$
	≥ 1	track-jet pairs	$\Delta R_{\text{track,jet}} > 0.5$
	≥ 1	tracks	$E_{\text{calo}} < 10 \text{ GeV}$
	≥ 1	tracks	missing outer hits ≥ 3

Table 6.16: Criteria defining the tau tag-and-probe sample with an electron tag. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
	event passes SingleElectron/EGamma triggers	
≥ 1	electrons	$p_{\text{T}} > 32 \text{ GeV}$
≥ 1	electrons	$ \eta < 2.1$
≥ 1	electrons	passing tight electron ID
≥ 1	electrons	$M_{\text{T}}(p_{\text{T}}^{\text{miss}}, \text{electron}) < 40 \text{ GeV}$
≥ 1	tracks	$p_{\text{T}} > 30 \text{ GeV}$
≥ 1	tracks	passing fiducial selections
≥ 1	tracks	number of pixel hits ≥ 4
≥ 1	tracks	missing inner hits = 0
≥ 1	tracks	missing middle hits = 0
≥ 1	tracks	rel. PF-based iso. < 0.05
≥ 1	tracks	$ d_{xy} < 0.02 \text{ cm}$
≥ 1	tracks	$ d_z < 0.5 \text{ cm}$
≥ 1	tracks	$\min \Delta R_{\text{track,electron}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track,muon}} > 0.15$
= 1	track-electron pairs	$15 \text{ GeV} < M_{\text{Z}} - M_{\text{track,electron}} < 50 \text{ GeV}$
= 1	track-electron pairs	$q_{\text{track}} \cdot q_{\text{electron}} < 0$
≥ 1	track	$n_{\text{layers}} \geq 4$ (three signal region bins)

Table 6.17: Criteria defining the tau tag-and-probe sample with an muon tag. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
event passes SingleMuon triggers		
≥ 1	muons	$p_T > 26 \text{ GeV}$
≥ 1	muons	$ \eta < 2.1$
≥ 1	muons	passing tight muon ID
≥ 1	muons	$M_T(p_T^{\text{miss}}, \text{muon}) < 40 \text{ GeV}$
≥ 1	tracks	$p_T > 30 \text{ GeV}$
≥ 1	tracks	passing fiducial selections
≥ 1	tracks	number of pixel hits ≥ 4
≥ 1	tracks	missing inner hits = 0
≥ 1	tracks	missing middle hits = 0
≥ 1	tracks	rel. PF-based iso. < 0.05
≥ 1	tracks	$ d_{xy} < 0.02 \text{ cm}$
≥ 1	tracks	$ d_z < 0.5 \text{ cm}$
≥ 1	tracks	$\min \Delta R_{\text{track}, \text{electron}} > 0.15$
≥ 1	tracks	$\min \Delta R_{\text{track}, \text{muon}} > 0.15$
$= 1$	track-muon pairs	$15 \text{ GeV} < M_Z - M_{\text{track}, \text{muon}} < 50 \text{ GeV}$
$= 1$	track-muon pairs	$q_{\text{track}} \cdot q_{\text{muon}} < 0$
≥ 1	track	$n_{\text{layers}} \geq 4$ (three signal region bins)

Table 6.18: Components used in the estimation of P_{veto} , and its value. $N_{\text{T\&P}}$ ($N_{\text{T\&P}}^{\text{veto}}$) and $N_{\text{SST\&P}}$ ($N_{\text{SST\&P}}^{\text{veto}}$) are the numbers of passing tag-probe pairs from the events in the nominal and same-sign tag-and-probe selections, respectively, before (after) the final vetoes are applied to the probe track.

run period	flavor	n_{layers}	$N_{\text{T\&P}}$	$N_{\text{T\&P}}^{\text{veto}}$	$N_{\text{SST\&P}}$	$N_{\text{SST\&P}}^{\text{veto}}$	P_{veto}
2022 CD	electron	4	33198	16	2193	16	$(0.0^{+1.8}_{-0.0}) \times 10^{-4}$
		5	83475	2	1832	2	$(0.0^{+2.5}_{-0.0}) \times 10^{-5}$
		≥ 6	1135112	18	3817	0	$(1.6 \pm 0.4) \times 10^{-5}$
2022 CD	muon	4	55	27	18	15	0.3 ± 0.2
		5	23	2	6	4	$0.0^{+0.067}_{-0.0}$
		≥ 6	1866959	1	64	1	$(0.0^{+7.6}_{-0.0}) \times 10^{-7}$
2022 CD	tau	4	48	11	24	15	$0.0^{+0.047}_{-0.0}$
		5	51	1	11	3	$0.0^{+0.028}_{-0.0}$
		≥ 6	3133	0	491	0	$(0.0^{+6.1}_{-0.0}) \times 10^{-4}$
2022 EFG	electron	4	66548	47	4615	42	$(8.1^{+15.2}_{-8.1}) \times 10^{-5}$
		5	172270	12	4318	8	$(2.4^{+2.7}_{-2.4}) \times 10^{-5}$
		≥ 6	2425839	32	8064	0	$(1.3 \pm 0.2) \times 10^{-5}$
2022 EFG	muon	4	200	87	86	75	0.1 ± 0.1
		5	104	15	26	20	$0.0^{+0.015}_{-0.0}$
		≥ 6	5264285	2	207	0	$(3.8 \pm 2.7) \times 10^{-7}$
2022 EFG	tau	4	95	21	36	20	$(1.7^{+10.9}_{-1.7}) \times 10^{-2}$
		5	102	5	9	2	$(3.2^{+2.9}_{-2.4}) \times 10^{-2}$
		≥ 6	4396	2	700	0	$(5.4^{+4.9}_{-3.8}) \times 10^{-4}$
2023 C	electron	4	58118	32	4222	35	$(0.0^{+2.1}_{-0.0}) \times 10^{-5}$
		5	166567	19	4453	10	$(5.6 \pm 3.3) \times 10^{-5}$
		≥ 6	2380183	34	8473	2	$(1.3 \pm 0.3) \times 10^{-5}$
2023 C	muon	4	179	92	86	81	$0.12^{+0.14}_{-0.12}$
		5	110	18	18	15	$0.03^{+0.06}_{-0.03}$
		≥ 6	4047502	3	149	1	$(4.9 \pm 4.9) \times 10^{-7}$
2023 C	tau	4	92	25	37	55	$0.0^{+0.031}_{-0.0}$
		5	126	10	32	15	$0.0^{+0.012}_{-0.0}$
		≥ 6	6822	1	1139	0	$(1.8^{+2.7}_{-1.8}) \times 10^{-4}$
2023 D	electron	4	28627	16	2134	24	$(0.0^{+4.3}_{-0.0}) \times 10^{-5}$
		5	82860	9	2275	9	$(0.0^{+5.3}_{-0.0}) \times 10^{-5}$
		≥ 6	1233525	4	4315	1	$(2.4 \pm 1.8) \times 10^{-6}$
2023 D	muon	4	108	55	62	60	$0.0^{+0.02}_{-0.0}$
		5	71	17	18	16	$0.02^{+0.11}_{-0.02}$
		≥ 6	2195110	2	111	0	$(9.1 \pm 6.4) \times 10^{-7}$
2023 D	tau	4	70	28	35	25	$0.09^{+0.20}_{-0.07}$
		5	53	5	19	8	$0.0^{+0.03}_{-0.0}$
		≥ 6	3296	0	599	2	$(0.0^{+4.2}_{-0.0}) \times 10^{-4}$

p_T^{miss} , so its p_T is summed to the event p_T^{miss} as in Equation 6.4 below (only for electrons and taus, since the muon p_T is already removed from p_T^{miss}):

$$p_T^{\text{miss, no mu}} \rightarrow |\vec{p}_T^{\text{miss, no mu}} + \vec{p}_T^l|. \quad (6.4)$$

The needed number of events are extracted from 2D plots of the control region $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})|$ and $p_T^{\text{miss, no } \mu}$ variables, as shown in Figure 6.15, where the red lines represent the offline requirements over the modified $p_T^{\text{miss, no } \mu}$. Only the single electron control region is shown due to its larger statistics in all three n_{layers} categories.

Probability to Pass the p_T^{miss} Triggers

P_{trigger} is derived from the events that passed conditions above and the signal trigger paths. The paths' efficiency $\epsilon(x)$ is defined as the probability of events from the single lepton control region to pass the triggers, and is used together with the $p_T^{\text{miss, no } \mu}$ distribution of single lepton events $n(x)$ to determine P_{trigger} as:

$$P_{\text{trigger}} = \frac{\int_{120 \text{ GeV}}^{\infty} n(x)\epsilon(x)dx}{\int_{120 \text{ GeV}}^{\infty} n(x)}. \quad (6.5)$$

The signal trigger efficiency and the $p_T^{\text{miss, no } \mu}$ distributions for the electron flavor are shown in Figures 6.16 and 6.17, respectively. Only the single electron control region is shown due to its larger statistics in all three n_{layers} categories.

Single Lepton Trigger Efficiencies

A final consideration in the normalization of the lepton background estimates is that the trigger requirements in the single lepton control regions may not be completely efficient. This leads to the underestimation of the number of events with charged leptons, and N_{ctrl}^l is corrected by dividing by the measured single lepton trigger efficiency for each flavor. The trigger efficiencies are measured using the tag-and-probe samples defined in Tables 6.8, 6.9, 6.16, and 6.17, with the additional requirement of the probe track having $p_T > 55 \text{ GeV}$. In these samples, the trigger efficiency, $\epsilon_{\text{trigger}}^l$, is defined as the probability for a probe track to be matched within $\Delta R < 0.3$ of an HLT object of the appropriate path for the flavor under study. Applying the same-sign subtraction technique as used for P_{veto} :

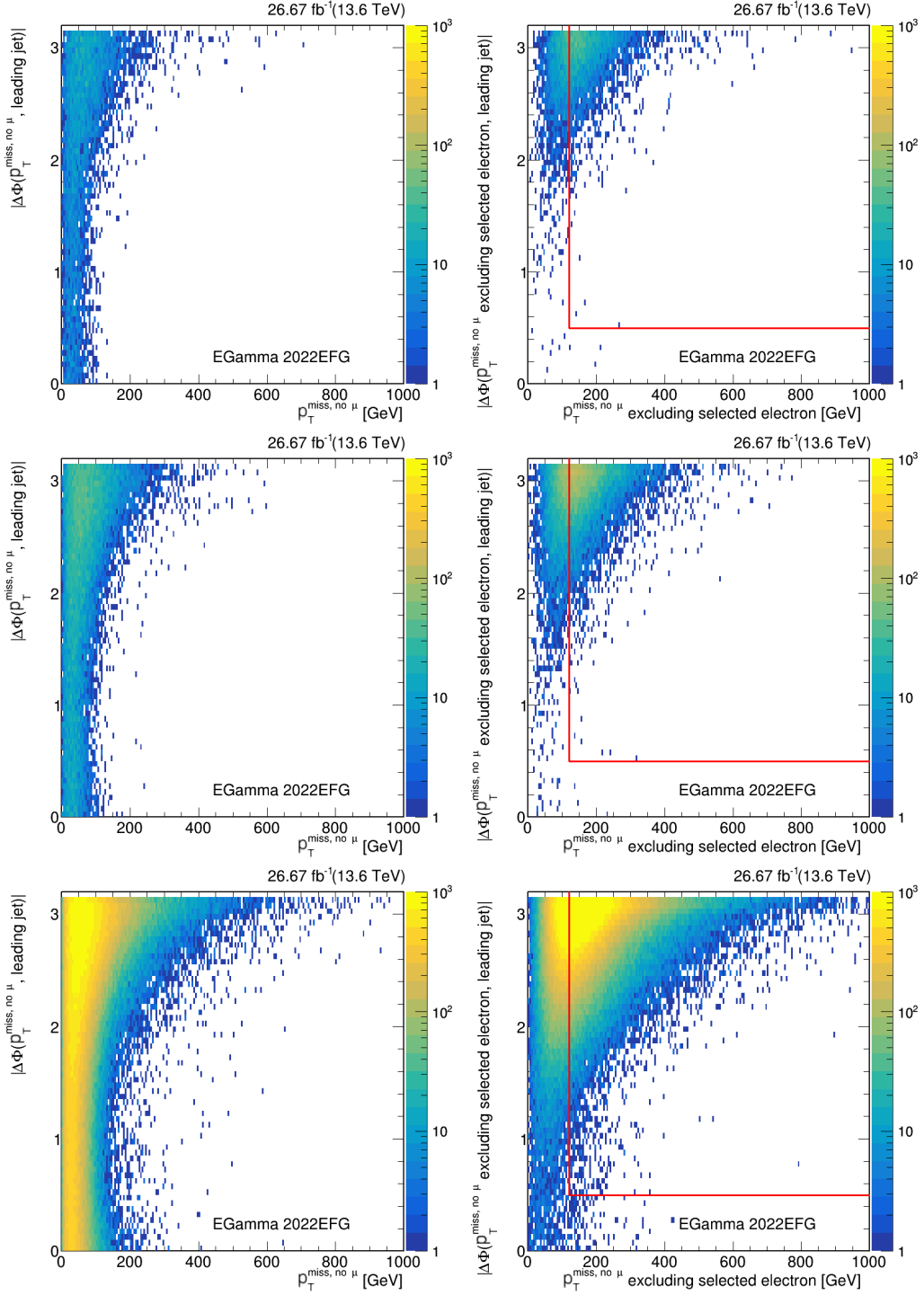


Figure 6.15: $p_T^{\text{miss, no } \mu}$ vs. $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})|$ of events in the single electron control region with $n_{\text{layers}} = 4$ (top), $n_{\text{layers}} = 5$ (middle), and $n_{\text{layers}} \geq 6$ (bottom), with the 2022EFG data set. Left (right) images show the $p_T^{\text{miss, no } \mu}$ distribution with the p_T of the electron counted as visible (invisible). Red lines are drawn where the offline $p_T^{\text{miss, no } \mu}$ and $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})|$ thresholds are set in the signal selection. P_{offline} is determined as the ratio of events falling in the upper right region to the total number of events.

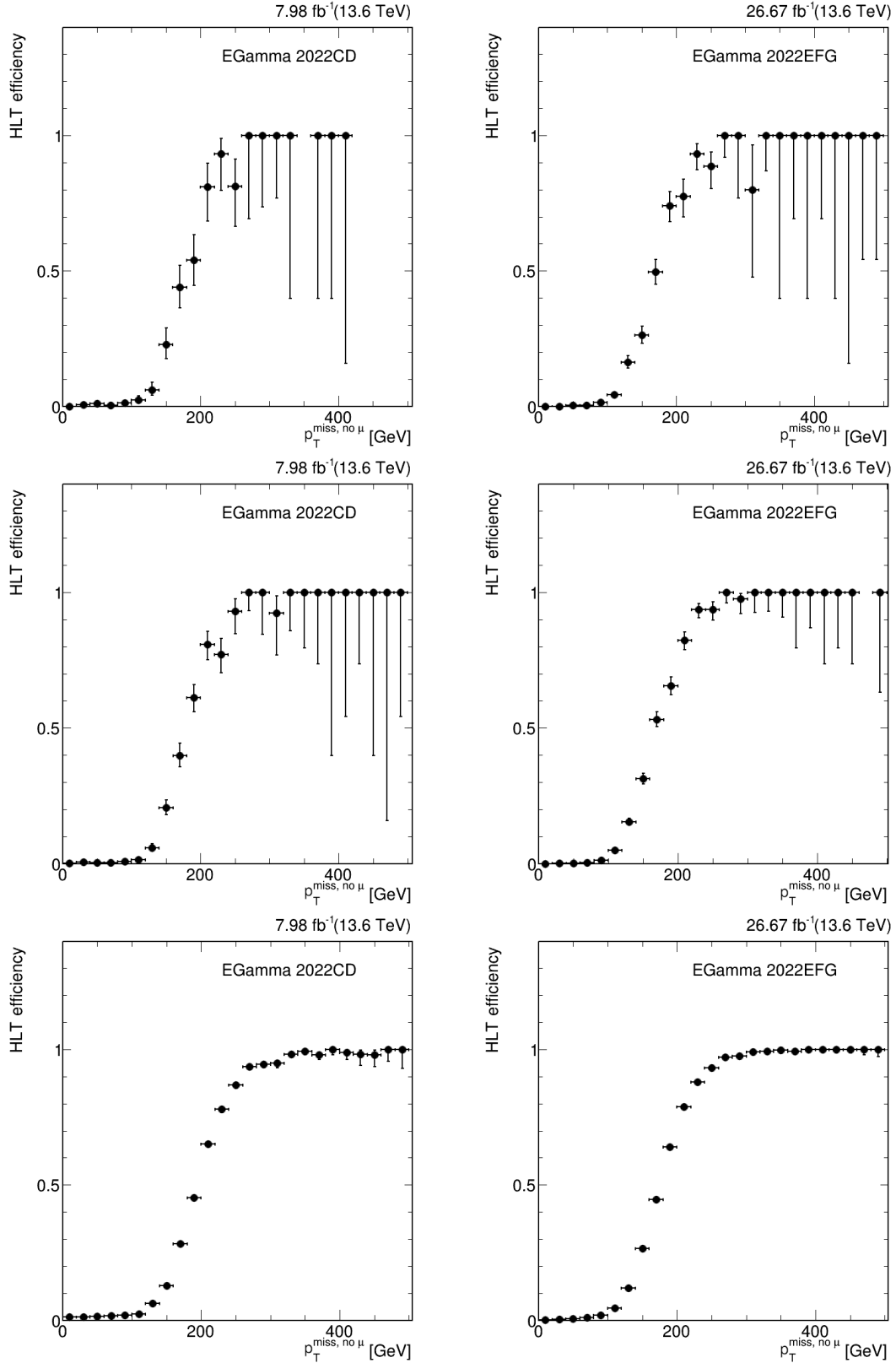


Figure 6.16: Efficiency of the p_T^{miss} triggers as a function of $p_T^{\text{miss, no } \mu}$ measured with events in the the single-electron control region with $n_{\text{layers}} = 4$ (top), $n_{\text{layers}} = 5$ (middle), and $n_{\text{layers}} \geq 6$ (bottom). Shown are the 2022CD data set (left) and the 2022EFG data set (right).

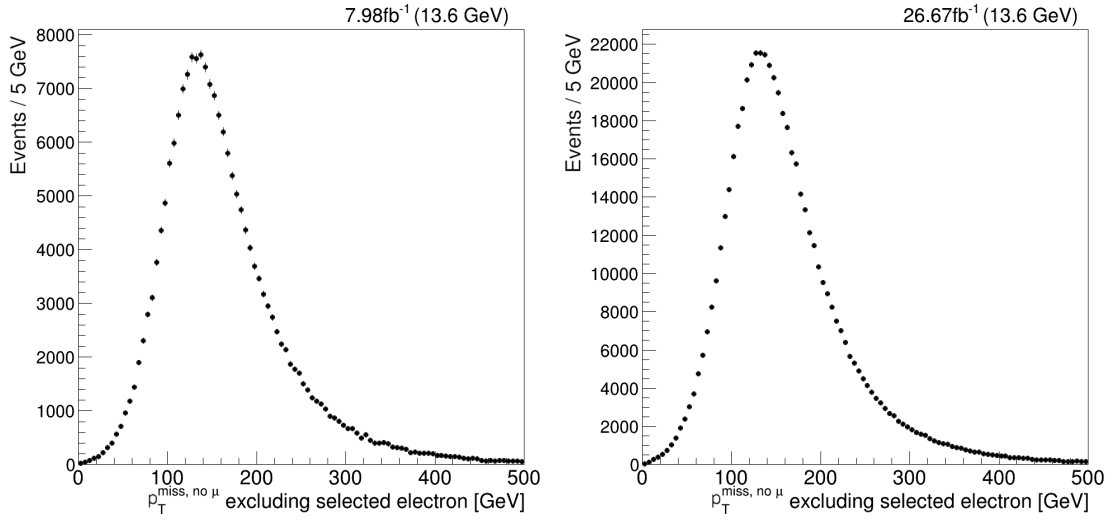


Figure 6.17: Projections of $p_T^{\text{miss, no } \mu}$ distributions from Section 6.3.1 used in the estimation of P_{trigger} . In the electron and tau cases, the distributions are modified by considering the lepton p_T as invisible. Events from Figure 6.15 that passed $|\Delta\Phi(\text{leading jet}, p_T^{\text{miss, no } \mu})| > 0.5$ are projected onto the x-axis, and the resulting distribution is multiplied by the trigger efficiencies. After the $p_T^{\text{miss, no } \mu} > 120$ GeV selection, the relative area of the projections gives P_{trigger} . Images show events in the $n_{\text{layers}} \geq 6$ signal with the single electron selections for 2022CD (left) and 2022EFG (right).

$$\epsilon_{\text{trigger}}^1 = \frac{N_{\text{T\&P } p_T > 55}^{\text{matched}} - N_{\text{SS T\&P } p_T > 55}^{\text{matched}}}{N_{\text{T\&P } p_T > 55} - N_{\text{SS T\&P } p_T > 55}} \quad (6.6)$$

where $N_{\text{T\&P } p_T > 55}$ ($N_{\text{T\&P } p_T > 55}^{\text{matched}}$) and $N_{\text{SS T\&P } p_T > 55}$ ($N_{\text{SS T\&P } p_T > 55}^{\text{matched}}$) are the numbers of passing tag-probe pairs from the events in the opposite- and same-sign tag-and-probe selections with the probe track having $p_T > 55$ GeV, respectively, before (after) requiring that the probe track is matched to the appropriate HLT primitive.

Additionally, in the case of the single tau lepton trigger, an extra factor is included due to the lack of a $p_T^\tau \sim 50$ GeV path in the Tau dataset. The option suggested by the dedicated CMS group was to utilize the path `HLT_IsoMu20_eta2p1_LooseDeepTauPFTauHPS27_eta2p1_CrossL1`, which selects events containing an isolated muon and a PF tau, from now on referred to as muon + tau path. However, this introduces the constraint in N_{ctrl}^τ that would be measured only if a muon was contained in the event. To estimate the single tau-only amount of N_{ctrl}^τ events, a scaling related to the usage of this path was applied using the efficiency of the single muon path `HLT_IsoMu20_eta2p1`, from now on referred to as muon path, to estimate the following ratio:

$$r_{\frac{\text{muon} + \text{tau}}{\text{tau}}} = \frac{\text{Efficiency of muon} + \text{tau path}}{\text{Efficiency of muon path}} = \frac{\epsilon_{\mu+\tau}}{\epsilon_\mu}. \quad (6.7)$$

Given that the efficiency of the muon + tau path is already included in the estimation of N_{ctrl}^τ , the scaling of N_{ctrl}^τ is performed by multiplying it by $1/\epsilon_\mu$.

Closure tests in simulated events

A closure test is performed to evaluate the lepton background estimation approach with simulated event samples corresponding to the 2022 conditions. Due to the restricted number of events satisfying the full search criteria, the test is executed under slightly relaxed selection requirements:

- all jet-related selections are omitted from the basic selection (see Table 6.6)
- the track p_T threshold is reduced from 55 GeV to 35 GeV (refer to Table 6.7) for electrons and muons
- the final criterion on missing outer hits for tracks is excluded (see Table 6.11)

The first two changes are applied to the single-lepton control regions used to derive N_{ctrl}^1 , and the removal of the missing outer hits requirement is done to the vetoes

within the lepton tag-and-probe samples (see Table 6.15). The quantity P_{veto} for each lepton type is subsequently extracted from the $Z \rightarrow \ell\ell$ datasets. Additionally, the final modification involves making use of the truth-level information present in the selected (observed) events to assign a lepton flavor to each selection, thus enabling each flavor comparison.

Except for the measurement of P_{veto} in the $Z \rightarrow \ell\ell$ datasets and the changes to the selections, the closure test is executed on simulated $t\bar{t}$ events following the same methodology as applied to data. The $t\bar{t}$ sample is chosen for this study due to its highest raw event count passing the modified selection, while contributions from other sources are negligible in comparison. The estimated and observed values of this validation are shown in Table 6.19.

Table 6.19: Lepton background closure test results using 2022 simulated $t\bar{t}$ events. The selection criteria are relaxed with respect to the one used over data. The numbers of events are normalized to 34.7 fb^{-1} , the luminosity of the 2022 data set.

n_{layers}	flavor	N_{est}^l	N_{obs}^l	$ N_{\text{est}}^l - N_{\text{obs}}^l /\sigma(N_{\text{est}}^l)$
4	electron	$0.08^{+0.11}_{-0.05}$	$0.0^{+0.07}_{-0.0}$	0.61
	muon	$0.01^{+0.02}_{-0.01}$	0.08 ± 0.07	1.00
	tau	$0.07^{+0.06}_{-0.05}$	0.16 ± 0.08	0.94
5	electron	$0.0^{+0.04}_{-0.0}$	$0.04^{+0.06}_{-0.04}$	0.55
	muon	$0.02^{+0.03}_{-0.02}$	$0.04^{+0.06}_{-0.04}$	0.33
	tau	$0.08^{+0.13}_{-0.08}$	$0.0^{+0.07}_{-0.0}$	0.53
≥ 6	electron	$0.0^{+0.07}_{-0.0}$	$0.04^{+0.06}_{-0.04}$	0.42
	muon	$0.0^{+0.08}_{-0.0}$	0.08 ± 0.07	0.74
	tau	$0.0^{+0.04}_{-0.0}$	$0.04^{+0.06}_{-0.04}$	0.57

Background Estimation

In Tables 6.20, 6.21, and 6.22, the values of all quantities mentioned above are displayed for the distinct lepton flavors and in the distinct SR regions. It is possible to notice that the amount of expected background events is very small. This is since this mainly comes from detector reconstruction failures in a detector that can reconstruct leptons with very high efficiency, and the very specific and constraining characteristics of the disappearing tracks signature.

Table 6.20: Background estimates in the electron control region for each n_{layers} category. Shown are the values of each variable in Equation 6.2, with the uncertainties being statistical only. Values of P_{offline} and P_{trigger} for the combination of the n_{layers} categories are included, given that systematic uncertainties for the muon and tau estimates have limited statistics and the electron samples are used.

run period	n_{layers}	$\epsilon_{\text{trigger}}^{\text{l}}$	electron background			P_{offline}	P_{trigger}	estimate
			$N_{\text{ctrl}}^{\text{l}}$	P_{veto}				
2022CD	4	0.751 ± 0.031	2896 ± 54	$(0.0^{+1.8}_{-0.0}) \times 10^{-4}$	0.644 ± 0.019	0.370 ± 0.048	$0.0^{+0.17}_{-0.0}$	
	5	0.856 ± 0.018	8121 ± 90	$(0.0^{+2.45}_{-0.0}) \times 10^{-5}$	0.655 ± 0.012	0.425 ± 0.033	$0.0^{+0.06}_{-0.0}$	
	≥ 6	0.912 ± 0.004	197621 ± 445	$(1.59 \pm 0.38) \times 10^{-5}$	0.724 ± 0.003	0.402 ± 0.006	1.01 ± 0.24	
	combined	0.906 ± 0.004	208638 ± 457	$(1.45 \pm 0.59) \times 10^{-5}$	0.721 ± 0.002	0.405 ± 0.006	0.97 ± 0.40	
2022EFG	4	0.683 ± 0.019	7588 ± 87	$(8.07^{+15.23}_{-8.07}) \times 10^{-5}$	0.635 ± 0.012	0.476 ± 0.034	$0.27^{+0.51}_{-0.27}$	
	5	0.835 ± 0.011	21858 ± 148	$(2.38^{+2.66}_{-2.38}) \times 10^{-5}$	0.645 ± 0.007	0.500 ± 0.021	$0.20^{+0.23}_{-0.20}$	
	≥ 6	0.895 ± 0.003	563302 ± 751	$(1.32 \pm 0.23) \times 10^{-5}$	0.712 ± 0.001	0.509 ± 0.004	3.02 ± 0.53	
	combined	0.888 ± 0.003	592748 ± 770	$(1.55 \pm 0.45) \times 10^{-5}$	0.708 ± 0.001	0.509 ± 0.004	3.73 ± 1.08	
2023C	4	0.691 ± 0.021	4625 ± 68	$(0.0^{+2.1}_{-0.0}) \times 10^{-5}$	0.634 ± 0.015	0.501 ± 0.045	$0.0^{+0.05}_{-0.0}$	
	5	0.810 ± 0.012	13715 ± 117	$(5.55 \pm 3.32) \times 10^{-5}$	0.657 ± 0.009	0.491 ± 0.024	0.30 ± 0.18	
	≥ 6	0.883 ± 0.003	377059 ± 614	$(1.35 \pm 0.25) \times 10^{-5}$	0.710 ± 0.002	0.531 ± 0.005	2.17 ± 0.41	
	combined	0.877 ± 0.003	395399 ± 629	$(1.47 \pm 0.44) \times 10^{-5}$	0.708 ± 0.002	0.530 ± 0.005	2.49 ± 0.75	
2023D	4	0.679 ± 0.029	2155 ± 46	$(0.0^{+4.3}_{-0.0}) \times 10^{-5}$	0.637 ± 0.022	0.428 ± 0.062	$0.0^{+0.04}_{-0.0}$	
	5	0.806 ± 0.018	6496 ± 81	$(0.0^{+5.3}_{-0.0}) \times 10^{-5}$	0.651 ± 0.013	0.504 ± 0.041	$0.0^{+0.14}_{-0.0}$	
	≥ 6	0.884 ± 0.004	189755 ± 436	$(2.44 \pm 1.82) \times 10^{-6}$	0.698 ± 0.003	0.532 ± 0.008	0.19 ± 0.15	
	combined	0.878 ± 0.004	198406 ± 445	$(0.0^{+8.52}_{-0.0}) \times 10^{-7}$	0.696 ± 0.002	0.532 ± 0.008	$0.0^{+0.07}_{-0.0}$	

Table 6.21: Background estimates in the muon control region for each n_{layers} category. Shown are the values of each variable in Equation 6.2, with the uncertainties being statistical only. Values of $\epsilon_{\text{trigger}}^1$, P_{offline} and P_{trigger} for the combination of the n_{layers} categories are included, given that the $n_{\text{layers}} = 4, 5$ categories have limited statistics and the combined value is used instead.

run period	n_{layers}	$\epsilon_{\text{trigger}}^1$	muon background			P_{offline}	P_{trigger}	estimate
			N_{ctrl}^1	P_{veto}				
2022CD	4	-	$0.0^{+1.1}_{-0.0}$	0.32 ± 0.19	-	-	$0.0^{+0.20}_{-0.0}$	
	5	-	$0.0^{+1.1}_{-0.0}$	$(0.0^{+6.70}_{-0.0}) \times 10^{-2}$	-	-	$0.0^{+0.03}_{-0.0}$	
	≥ 6	0.94 ± 0.004	$168\,145 \pm 410$	$(0.0^{+7.58}_{-0.0}) \times 10^{-7}$	0.766 ± 0.003	0.655 ± 0.004	$0.0^{+0.07}_{-0.0}$	
	combined	0.94 ± 0.004	168145 ± 410	$(5.36 \pm 3.79) \times 10^{-6}$	0.766 ± 0.003	0.655 ± 0.004	0.48 ± 0.34	
2022EFG	4	-	2.0 ± 1.4	0.11 ± 0.11	-	-	$0.12^{+0.15}_{-0.12}$	
	5	-	2.0 ± 1.4	$(0.0^{+1.46}_{-0.0}) \times 10^{-2}$	-	-	$0.0^{+0.02}_{-0.0}$	
	≥ 6	0.94 ± 0.004	489703 ± 700	$(3.80 \pm 2.69) \times 10^{-7}$	0.745 ± 0.002	0.696 ± 0.003	0.10 ± 0.07	
	combined	0.94 ± 0.004	489707 ± 700	$(1.71^{+2.68}_{-1.71}) \times 10^{-6}$	0.745 ± 0.002	0.696 ± 0.003	$0.46^{+0.72}_{-0.46}$	
2023C	4	-	1.0 ± 1.0	$0.12^{+0.14}_{-0.12}$	-	-	$0.07^{+0.10}_{-0.07}$	
	5	-	1.0 ± 1.0	$(3.26^{+6.26}_{-3.26}) \times 10^{-2}$	-	-	$0.02^{+0.04}_{-0.02}$	
	≥ 6	0.94 ± 0.003	$307\,476 \pm 555$	$(4.94 \pm 4.94) \times 10^{-7}$	0.747 ± 0.002	0.708 ± 0.003	0.09 ± 0.09	
	combined	0.94 ± 0.002	$307\,478 \pm 555$	$(3.95 \pm 3.58) \times 10^{-6}$	0.747 ± 0.002	0.708 ± 0.003	0.68 ± 0.62	
2023D	4	-	$0.0^{+1.1}_{-0.0}$	$(0.0^{+2.48}_{-0.0}) \times 10^{-2}$	-	-	$0.0^{+0.01}_{-0.0}$	
	5	-	$0.0^{+1.1}_{-0.0}$	$(1.89^{+10.84}_{-1.89}) \times 10^{-2}$	-	-	$0.0^{+0.01}_{-0.0}$	
	≥ 6	0.94 ± 0.003	$157\,934 \pm 397$	$(9.11 \pm 6.44) \times 10^{-7}$	0.736 ± 0.003	0.721 ± 0.005	0.08 ± 0.06	
	combined	0.94 ± 0.003	$157\,934 \pm 397$	$(0.0^{+5.19}_{-0.0}) \times 10^{-7}$	0.736 ± 0.003	0.721 ± 0.005	$0.0^{+0.05}_{-0.0}$	

Table 6.22: Background estimates in the tau control region for each n_{layers} category. Shown are the values of each variable in Equation 6.2, with the uncertainties being statistical only. Values of $\epsilon_{\text{trigger}}^1$, P_{offline} and P_{trigger} for the combination of the n_{layers} categories are included, given that the $n_{\text{layers}} = 4, 5$ categories have limited statistics and the combined value is used instead.

run period	n_{layers}	$\epsilon_{\text{trigger}}^1$	tau background		P_{veto}	P_{offline}	P_{trigger}	estimate
2022CD	4	-	0.013	3.0 ± 1.7	$0.0^{+0.047}_{-0.0}$	-	-	$0.0^{+0.016}_{-0.0}$
	5	-	0.013	2.0 ± 1.4	$0.0^{+0.028}_{-0.0}$	-	-	$0.0^{+0.0064}_{-0.0}$
	≥ 6	0.90 ± 0.01	0.013	265 ± 16	$(0.0^{+6.1}_{-0.0}) \times 10^{-4}$	0.208 ± 0.031	0.46 ± 0.1	$0.0^{+0.017}_{-0.0}$
	combined	0.90 ± 0.01	0.013	270 ± 16	$(0.0^{+4.2}_{-0.0}) \times 10^{-4}$	0.215 ± 0.031	0.47 ± 0.1	$0.0^{+0.011}_{-0.0}$
2022EFG	4	-	0.016	10 ± 3	$(1.69^{+10.9}_{-1.69}) \times 10^{-2}$	-	-	$0.03^{+0.16}_{-0.03}$
	5	-	0.016	21 ± 5	$(3.22^{+2.87}_{-2.43}) \times 10^{-2}$	-	-	$0.10^{+0.09}_{-0.08}$
	≥ 6	0.90 ± 0.01	0.016	902 ± 30	$(5.41^{+4.91}_{-3.83}) \times 10^{-4}$	0.235 ± 0.018	0.552 ± 0.060	$0.11^{+0.10}_{-0.08}$
	combined	0.90 ± 0.01	0.016	933 ± 31	$(1.56^{+2.84}_{-1.56}) \times 10^{-3}$	0.240 ± 0.018	0.562 ± 0.061	$0.33^{+0.39}_{-0.33}$
2023C	4	-	0.015	5.0 ± 2.2	$0.0^{+0.03}_{-0.0}$	-	-	$0.0^{+0.03}_{-0.0}$
	5	-	0.015	10.0 ± 3.2	$0.0^{+0.012}_{-0.0}$	-	-	$0.0^{+0.02}_{-0.0}$
	≥ 6	0.90 ± 0.01	0.015	530 ± 23	$(1.76^{+2.67}_{-1.76}) \times 10^{-4}$	0.257 ± 0.025	0.581 ± 0.080	$0.02^{+0.04}_{-0.02}$
	combined	0.90 ± 0.01	0.015	545 ± 23	$(0.0^{+2.0}_{-0.0}) \times 10^{-4}$	0.261 ± 0.025	0.578 ± 0.078	$0.0^{+0.017}_{-0.0}$
2023D	4	-	0.014	5.0 ± 2.2	$0.086^{+0.210}_{-0.069}$	-	-	$0.07^{+0.19}_{-0.07}$
	5	-	0.014	6.0 ± 2.4	$0.0^{+0.033}_{-0.0}$	-	-	$0.0^{+0.035}_{-0.0}$
	≥ 6	0.90 ± 0.01	0.014	290 ± 17	$(0.0^{+4.2}_{-0.0}) \times 10^{-4}$	0.262 ± 0.034	0.580 ± 0.106	$0.0^{+0.021}_{-0.0}$
	combined	0.90 ± 0.01	0.014	301 ± 17	$(0.0^{+4.1}_{-0.0}) \times 10^{-4}$	0.276 ± 0.034	0.569 ± 0.102	$0.0^{+0.019}_{-0.0}$

6.3.2 Fake Tracks

Spurious tracks, also known as fake tracks, are tracks reconstructed from hits that come from distinct real particles. Their main features are: usually do not come from the region close to the primary vertex, have missing inner hits in a random pattern, have little calorimeter energy associated with the track, and have a higher number of missing outer hits. The last two characteristics make these tracks good disappearing tracks candidates, but which do not come from real particles and need to be accounted for as a background. The estimation of the number of expected fake tracks is also done with probabilities. In this case, the amount of events that contain a fake track is compared with control events that most definitely do not contain real disappearing tracks candidates using Equation 6.8 below:

$$N_{\text{est}}^{\text{fake}} = \zeta \cdot P_{\text{fake}}^{\text{raw}} \cdot N_{\text{ctrl}}^{\text{basic}}, \quad (6.8)$$

where $N_{\text{ctrl}}^{\text{basic}}$ is the number of events passing the basic selection defined in Table 6.6, and P_{fake} and ζ are defined below.

The selections used to define control regions that are clean of disappearing tracks candidates come from $Z \rightarrow \mu\mu$ and $Z \rightarrow ee$ selections, and are defined in Tables 6.23 and 6.24, respectively. Given the higher distance from the primary vertex, the fake tracks are further selected passing the disappearing tracks selection (Table 6.11), but with the d_0 requirement "inverted", that is, instead of selecting tracks within $|d_0| < 0.02$ cm, the fake tracks are selected within the side-bands $0.05 \text{ cm} < |d_0| < 0.5$ cm. $P_{\text{fake}}^{\text{raw}}$ is then defined as the fraction of the number of disappearing tracks in the side-band region that passed through the control region selection, divided by the number of events in the control region, as shown in Equation 6.9:

$$P_{\text{fake}}^{\text{raw}} \equiv \frac{N(\geq 1 \text{ disappearing track in sideband} \mid \text{control region})}{N(\text{control region})}. \quad (6.9)$$

Table 6.23: Criteria defining the $Z \rightarrow \mu\mu$ control sample. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
	event passes SingleMuon triggers	
= 2	muons	$p_T > 26 \text{ GeV}$
= 2	muons	$ \eta < 2.1$
= 2	muons	passes tight muon ID
= 1	muon pairs	$q_{\text{muon}} \cdot q_{\text{muon}} < 0$
= 1	muon pairs	$ M_{\text{muon,muon}} - M_Z < 10 \text{ GeV}$

The amount of fake tracks is more pronounced in the $n_{\text{layers}} = 4$ category, given the large amount of missing inner, middle, and outer hits in this type of track. To calculate the estimates for 5 and 6 or more bins, the transfer factor ζ is used, which normalizes the signal region by the sideband region as:

$$\zeta = \frac{\int_0^{0.02 \text{ cm}} \text{fit } d(|d_0|)}{\int_{0.05 \text{ cm}}^{0.5 \text{ cm}} \text{fit } d(|d_0|)} \quad (6.10)$$

where the fit is performed over the tracks' $|d_0|$ distribution using a Gaussian + constant function, in the range $0.1 \text{ cm} < |d_0| < 0.5 \text{ cm}$ while fixing the mean to be zero. Figure 6.18 shows the distribution of the $|d_0|$ variable for tracks with $n_{\text{layers}} = 4$ in the four data-taking periods that passed through the $Z \rightarrow \mu\mu$ and $Z \rightarrow ee$

Table 6.24: Criteria defining the $Z \rightarrow ee$ control sample. The selections are applied sequentially, with only the objects passing a given selection being used in further requirements.

quantity	object	selection
	event passes SingleElectron triggers	
≥ 1	electrons	$p_T > 32 \text{ GeV}$
$= 2$	electrons	$p_T > 25 \text{ GeV}$
$= 2$	electrons	$ \eta < 2.1$
$= 2$	electrons	passes tight electron ID
$= 1$	electron pairs	$q_{\text{electron}} \cdot q_{\text{electron}} < 0$
$= 1$	electron pairs	$ M_{\text{electron,electron}} - M_Z < 10 \text{ GeV}$

selections. The result of the fit is shown with the full line for each period/selection.

Closure tests in simulated events

To test the robustness of the methodology used to estimate the background from fake tracks, a closure test is performed using simulated background events. The procedure mimics that applied to experimental data in the $Z \rightarrow \mu\mu$ control region, utilizing all SM MC samples. The result is then compared to the actual count of events in these samples that contain a track passing the disappearing track selection and that exhibits a separation of $\Delta R > 0.1$ from any generator-level particle with $p_T > 10 \text{ GeV}$. This evaluation is performed individually for each of the three n_{layers} categories, with the exception of the $n_{\text{layers}} \geq 6$ region, where the number of events is not enough for a relevant comparison. The results are presented in Table 6.25. For every region considered, agreement is obtained within 2.2σ , excluding the systematic uncertainty associated with the fit used to derive the transfer factor. The d_{xy} distribution for tracks in the $n_{\text{layers}} = 4$ control region is illustrated in Figure 6.19, where the result of the fit is included in the image.

Background Estimation

In Table 6.26, there are the results for the estimated number of fake tracks. As already mentioned, the number of fake tracks is largest in $n_{\text{layers}} = 4$, and decreases to close to zero in $n_{\text{layers}} = 6$ or more. This is expected due to the characteristics of the fake tracks and the very constraining properties of a real disappearing track.

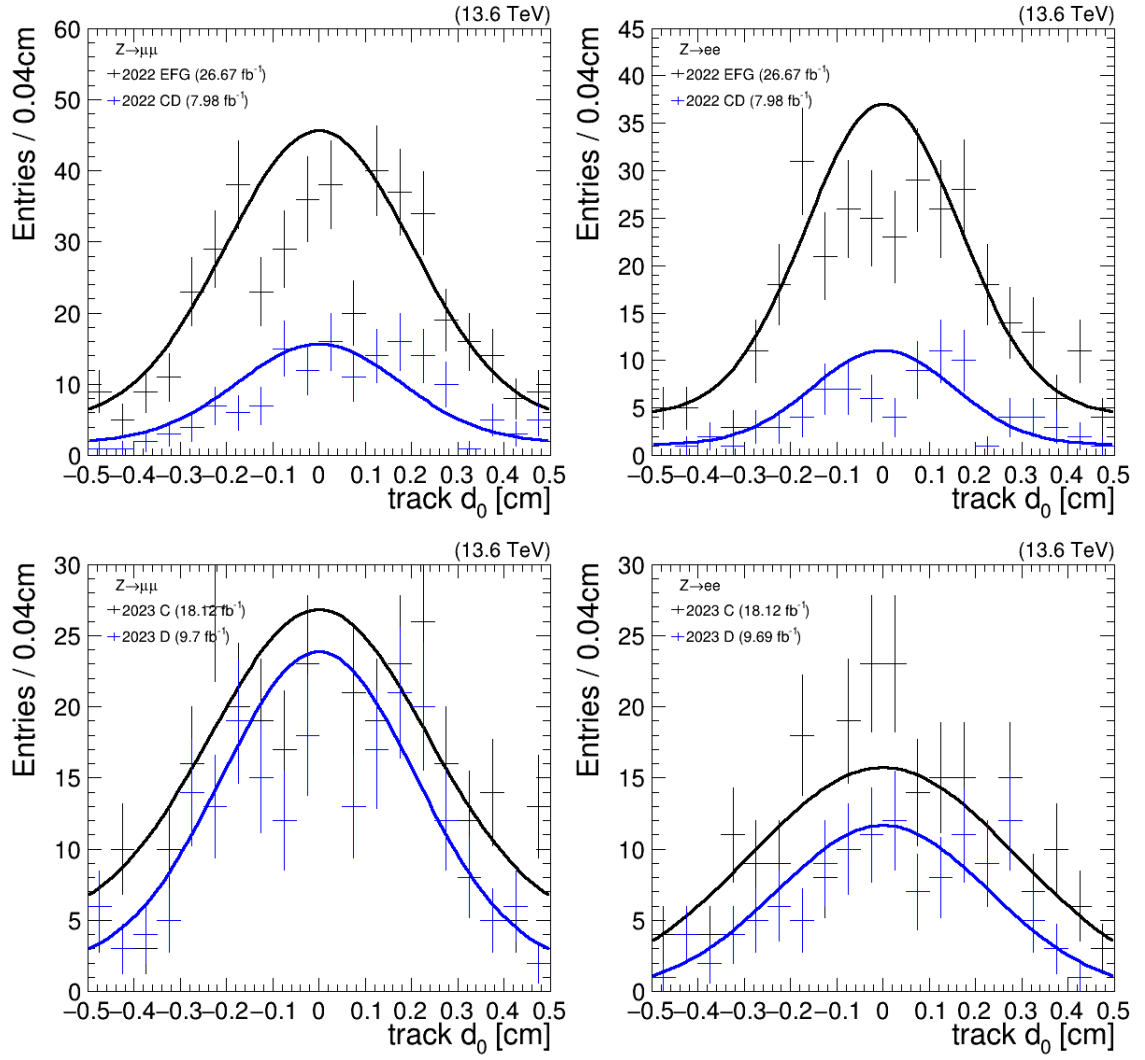


Figure 6.18: $|d_0|$ distributions for 2022 (top) and 2023 (events) tracks that passed the $Z \rightarrow \mu\mu$ (left) and $Z \rightarrow ee$ (right) selections. The category considered is for tracks with $n_{\text{layers}} = 4$. The full lines represent the result of the Gaussian + constant fit performed to extract ζ .

Table 6.25: Fake tracks background closure test results. Results of the closure test for the fake track background estimate in 2022 simulated background events. The uncertainties are statistical and do not include the uncertainty from the fit used to extract the transfer factor.

n_{layers}	$N_{\text{est}}^{\text{fake}}$	$N_{\text{obs}}^{\text{fake}}$	$ N_{\text{est}}^{\text{fake}} - N_{\text{obs}}^{\text{fake}} / \sigma(N_{\text{est}}^{\text{fake}})$
4	7.8 ± 1.6	7.3 ± 5.0	0.1
5	2.3 ± 0.9	0.3 ± 0.1	2.2
≥ 6	insufficient statistics		

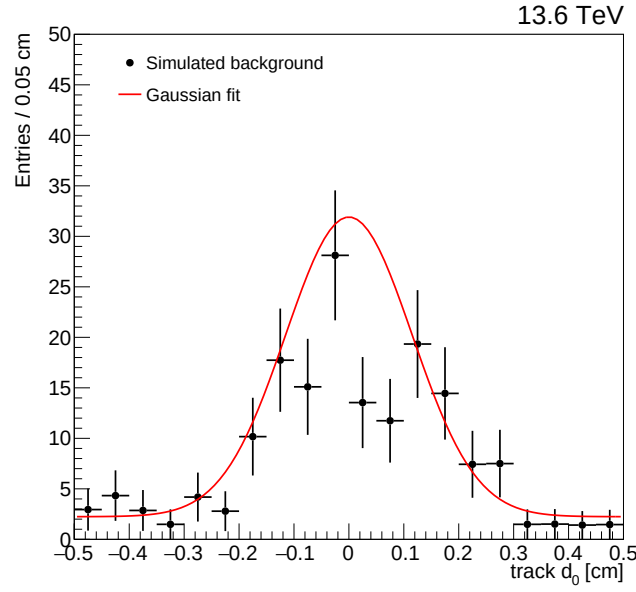


Figure 6.19: Distribution of d_{xy} for tracks in the $n_{\text{layers}} = 4$ control region in 2022 simulated background events. The red line shows the result of the Gaussian + constant fit to this distribution.

Table 6.26: Fake track event probabilities P_{fake} and estimations $N_{\text{est}}^{\text{fake}}$ obtained from events from $Z \rightarrow ee$ and $Z \rightarrow \mu\mu$ control regions, with the uncertainties being statistical only. The mean value of the fake tracks estimate is taken from the $Z \rightarrow \mu\mu$ control region, while the difference of the $Z \rightarrow \mu\mu$ with the $Z \rightarrow ee$ values is used as a systematic uncertainty, described in 6.5.1.

run period	n_{layers}	P_{fake}		$N_{\text{est}}^{\text{fake}}$	
		$Z \rightarrow \mu\mu$	$Z \rightarrow ee$	$Z \rightarrow \mu\mu$	$Z \rightarrow ee$
2022CD	4	$(3.93 \pm 2.37) \times 10^{-6}$	$(4.19 \pm 0.49) \times 10^{-6}$	5.28 ± 3.18	5.63 ± 0.66
	5	$(4.40 \pm 2.88) \times 10^{-7}$	$(2.87 \pm 1.28) \times 10^{-7}$	0.59 ± 0.39	0.39 ± 0.17
	≥ 6	$(3.14^{+3.66}_{-3.14}) \times 10^{-8}$	$(5.74 \pm 5.74) \times 10^{-8}$	$0.04^{+0.05}_{-0.04}$	0.08 ± 0.08
2022EFG	4	$(3.15 \pm 1.25) \times 10^{-6}$	$(5.17 \pm 0.31) \times 10^{-6}$	15.31 ± 6.09	25.08 ± 1.52
	5	$(4.40 \pm 1.84) \times 10^{-7}$	$(6.67 \pm 1.13) \times 10^{-7}$	2.13 ± 0.89	3.24 ± 0.55
	≥ 6	$(1.69 \pm 1.37) \times 10^{-8}$	$(1.91 \pm 1.91) \times 10^{-8}$	0.08 ± 0.07	0.09 ± 0.09
2023C	4	$(2.79 \pm 1.64) \times 10^{-6}$	$(2.84 \pm 2.69) \times 10^{-6}$	8.21 ± 4.81	8.34 ± 7.90
	5	$(6.88 \pm 4.09) \times 10^{-7}$	$(7.72 \pm 7.37) \times 10^{-7}$	2.02 ± 1.20	2.27 ± 2.17
	≥ 6	$0.0^{+1.15}_{-0.0} \times 10^{-8}$	$(1.58^{+2.17}_{-1.58}) \times 10^{-8}$	$0.0^{+0.03}_{-0.0}$	$0.05^{+0.06}_{-0.05}$
2023D	4	$(4.24 \pm 2.52) \times 10^{-6}$	$(4.53 \pm 2.32) \times 10^{-6}$	6.62 ± 3.93	7.06 ± 3.62
	5	$(1.09 \pm 0.66) \times 10^{-6}$	$(7.10 \pm 3.98) \times 10^{-7}$	1.70 ± 1.03	1.11 ± 0.62
	≥ 6	$(4.35 \pm 4.01) \times 10^{-8}$	$(1.33 \pm 1.02) \times 10^{-7}$	0.07 ± 0.06	0.21 ± 0.16

6.4 Signal Corrections

To correctly estimate the number of expected signal events, a number of MC-to-data corrections need to be included. In this analysis, four sources of corrections were accounted for:

- Differences in the trigger efficiency from MC to data, given that the MC distributions are more resolved and cause the turn-on curve to rise earlier/faster;
- Differences in the PU distribution, since the MC estimate does not always match the one obtained from data because the LHC conditions can change abruptly;
- Differences in the number of missing hits, given that the MC simulation is always more "optimistic" than data;
- Differences in the ISR p_T when comparing the distribution of this variable in data and MC;

Apart from the missing hits probability, which is corrected by changing the MC probability values to be closer to the data values and re-calculating the missing hits amount, the other three corrections are applied via scale factors (SFs) from $\frac{\text{data}}{\text{MC}}$ comparisons.

6.4.1 Trigger Efficiency

To calculate the trigger efficiency, a few assumptions are made: all of the signal paths' rely on some type of p_T^{miss} , so, to use SM events that are optimal for the calculation and that are orthogonal to the signal data, i.e., that are not collected using the p_T^{miss} paths, the single muon datasets are used (in MC, $W \rightarrow l\nu$ samples are used); the interesting region in the trigger efficiency is essentially the plateau of the track p_T , since that is the track p_T requirement in the signal region selection. To isolate this region, a set of base trigger selections that are defined in Table 6.27, one of which is that $p_T^\mu > 55$ GeV, are applied over the events used to measure the trigger efficiencies.

In Figure 6.20, the efficiency of the logical OR of the signal trigger paths is displayed for data and MC. The efficiency is calculated as a function of $p_T^{\text{miss, no } \mu}$, and divides the number of events passing the triggers and the base selections, by events that only passed the base selection. As already mentioned, the distinction in the turn-on curve for data and MC is noticeable, since the MC efficiency tends

Table 6.27: Base trigger selection used to select events used to measure the efficiency of the signal region triggers.

quantity	object	selection
event passes SingleMuon triggers		
≥ 1	muons	$p_T > 55 \text{ GeV}$
≥ 1	muons	$ \eta < 2.1$
≥ 1	muons	passing tight muon ID (see Table 6.4)
≥ 1	muons	missing inner hits = 0
≥ 1	muons	missing middle hits = 0

to rise earlier. The data over MC ratio provides the scale factors that are applied to signal MC events. Figure 6.21 shows the difference in $p_T^{\text{miss, no } \mu}$ for signal samples of 100 GeV and 700 GeV wino-like charginos with $c\tau = 10000 \text{ cm}$, before and after applying the trigger correction scale factors. The signal yields are reduced by $\sim 25\%$ and $\sim 15\%$ for the 100 and 700 GeV charginos, respectively.

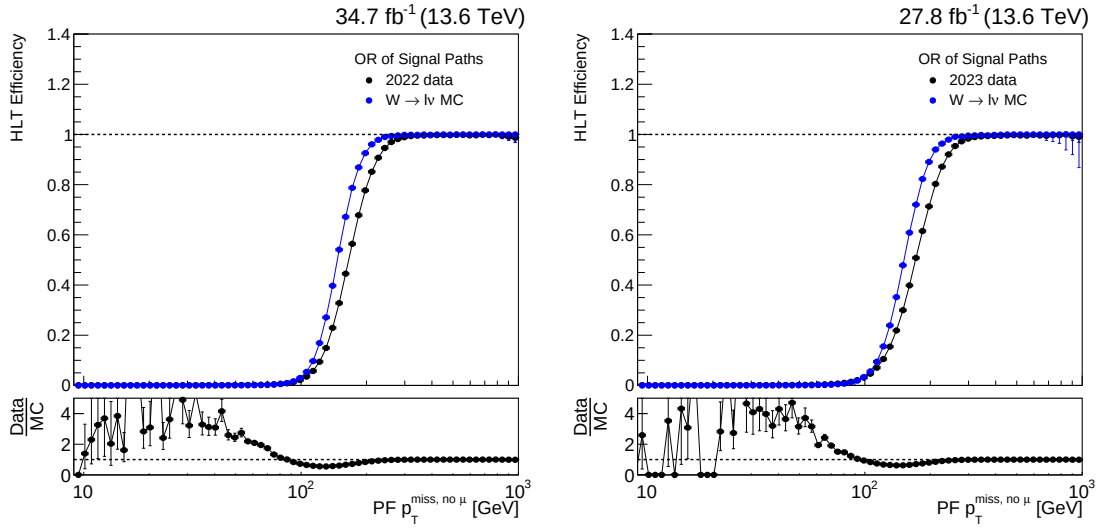


Figure 6.20: Efficiency of p_T^{miss} triggers with simulated $W \rightarrow l\nu$ and collected data from the whole period of 2022 (left) and 2023 (right). The efficiency is plotted only with respect to $p_T^{\text{miss, no } \mu}$, with the dependence on the track p_T integrated out by requiring $p_T^{\text{track}} > 55 \text{ GeV}$. The ratio between data and MC is shown in the subplot.

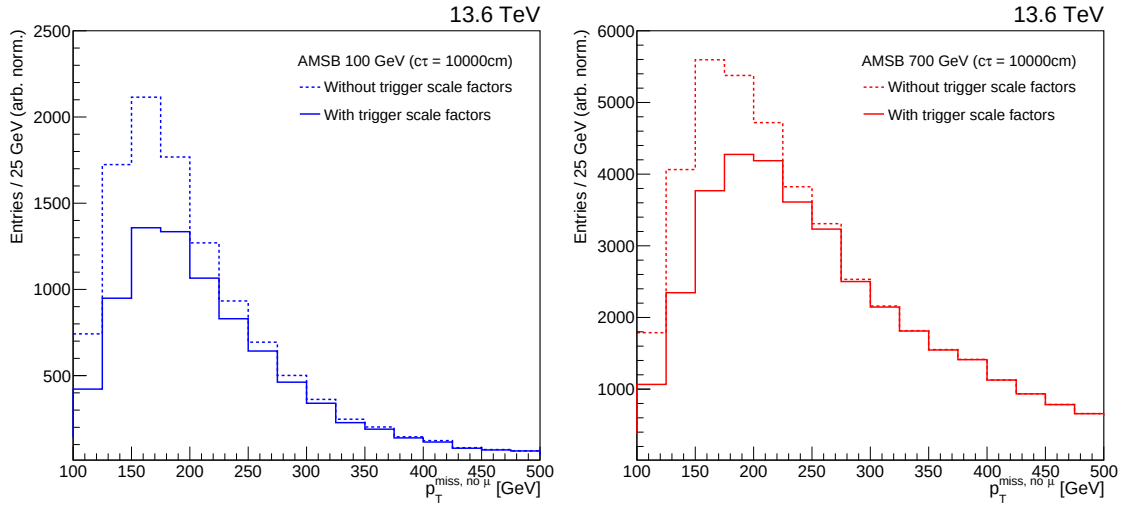


Figure 6.21: Distributions of $p_T^{\text{miss, no } \mu}$ with and without the trigger efficiency scale factors for the 2022 period applied with no requirements needed. Simulated signal events passing the triggers are plotted, with a 100 GeV chargino in the left plot and a 700 GeV chargino in the right plot.

6.4.2 PU Correction

The scale factors of the PU correction are extracted from the PU distributions of MC and data. In Figure 6.22, the PU distributions of MC and data for 2022 and 2023 are compared. Data PU distribution was extracted from muon datasets, and MC PU distribution was extracted from $W \rightarrow l\nu$ samples.

6.4.3 ISR p_T

Correcting the $p_T^{\text{miss, no } \mu}$ involves finding the ISR p_T , since, in the disappearing tracks signature, one recoils against the other. In data and MC, the ISR is assumed to be recoiling against a Z boson, and the correction is estimated as the dimuon p_T from events that contain a Z boson and one high p_T jet recoiling against the $p_T^{\text{miss, no } \mu}$. The correction comes from the dimuon p_T since its resolution is better than the ISR p_T and the $p_T^{\text{miss, no } \mu}$. Figure 6.23 shows the distribution of the dimuon p_T of the selected events. The data and MC ratio plot shows the scale factors that are applied over the signal MC for this correction.

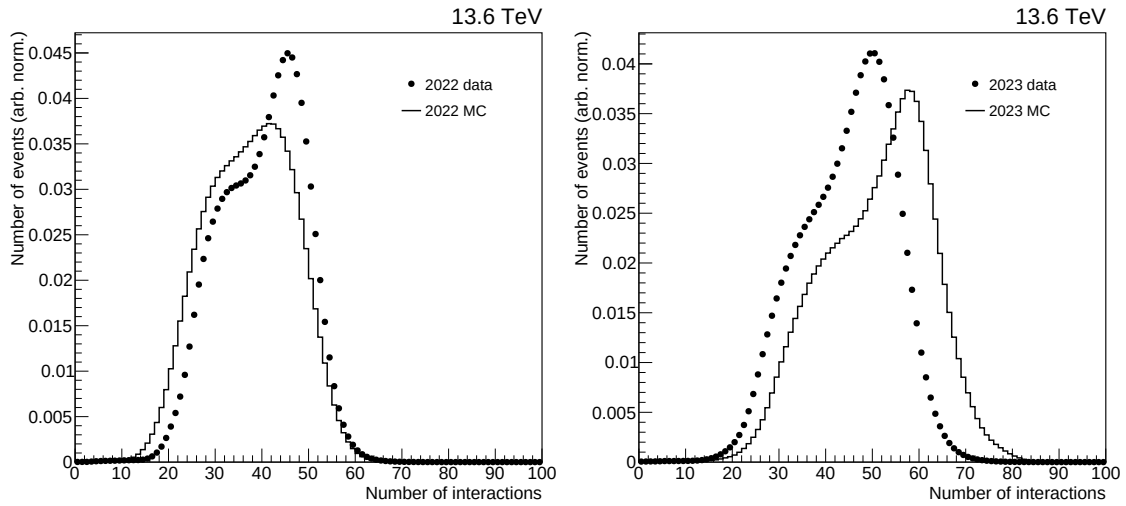


Figure 6.22: Number of interactions distributions with the whole 2022 (left) and 2023 (right) data sets for experimental (black circles) and simulated (black lines) samples.

6.4.4 Missing Hits

The number of missing middle and outer hits on candidate tracks is used to discriminate against background sources. However, as seen in Figures 6.24 and 6.25, comparisons of events from the muon control region show that the simulation does not model these missing hits accurately, particularly for tracks with three or more missing outer hits, which define the search region. Events from collected data sets show a higher probability of missing hits compared to simulation, especially around six missing outer hits. This discrepancy comes from a mismodeling in the track extrapolation between the TIB and TOB detector regions, where the TOB has six layers that can contribute to several missing outer hits when extrapolation fails.

While background estimates are drawn directly from experimental data and are unaffected by this modeling issue, the signal selection efficiencies rely on simulation and are therefore impacted. To address this, the missing outer hits distribution in simulation is corrected by randomly removing hits at a rate tuned to better match the experimental data. This correction aims to provide more realistic estimates of the signal acceptance, improving the reliability of the results.

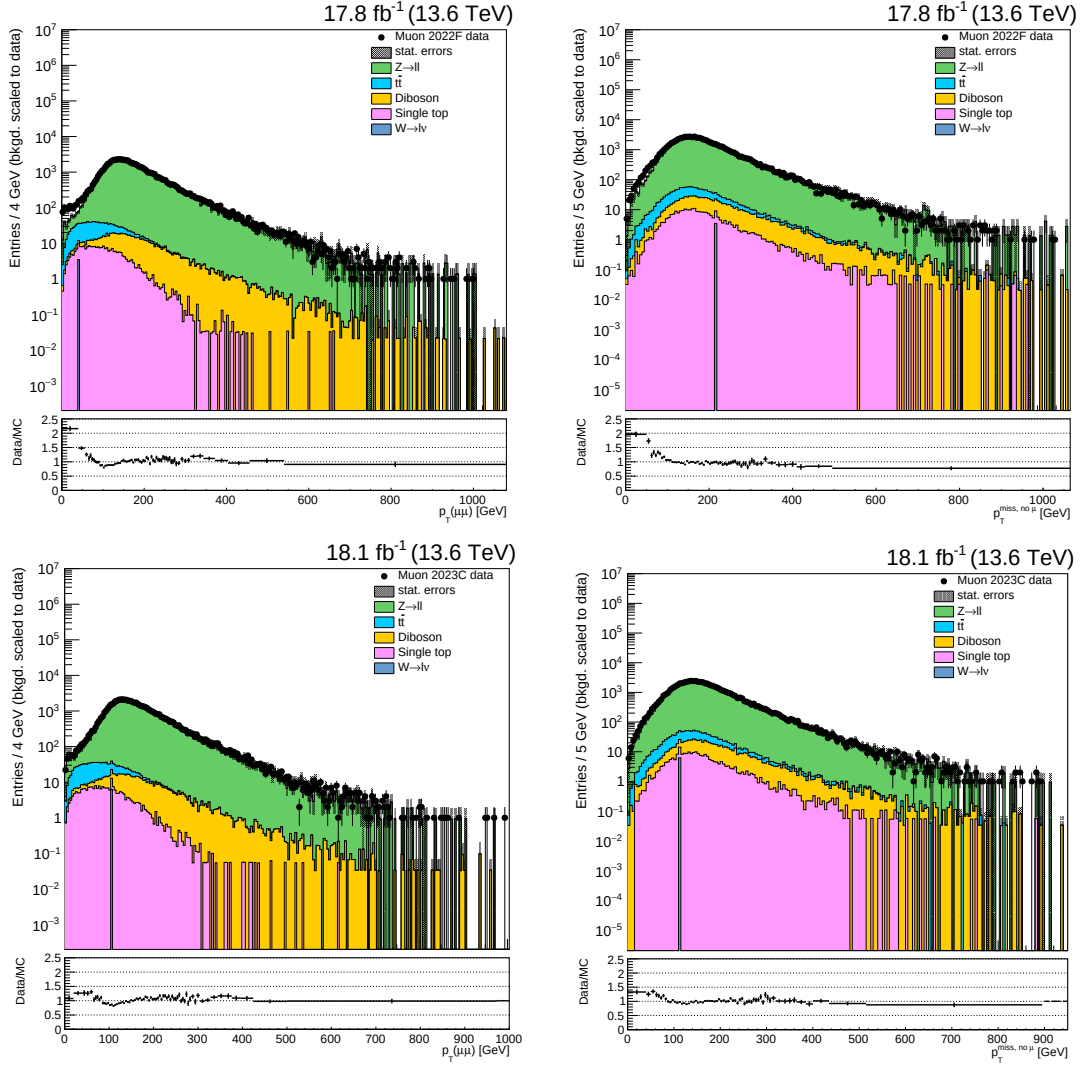


Figure 6.23: p_T of $Z \rightarrow \mu\mu$ candidates (left) and $p_T^{\text{miss, no } \mu}$ (right) distributions with events from the $Z \rightarrow \mu\mu$ control region for collected and simulated data before the ISR scale factors have been applied. The ratio plot shown below the $p_T(\mu\mu)$ plots is used as the ISR scale factors applied to the simulated events. Shown are the 2022F (top) and 2023C (bottom) data sets.

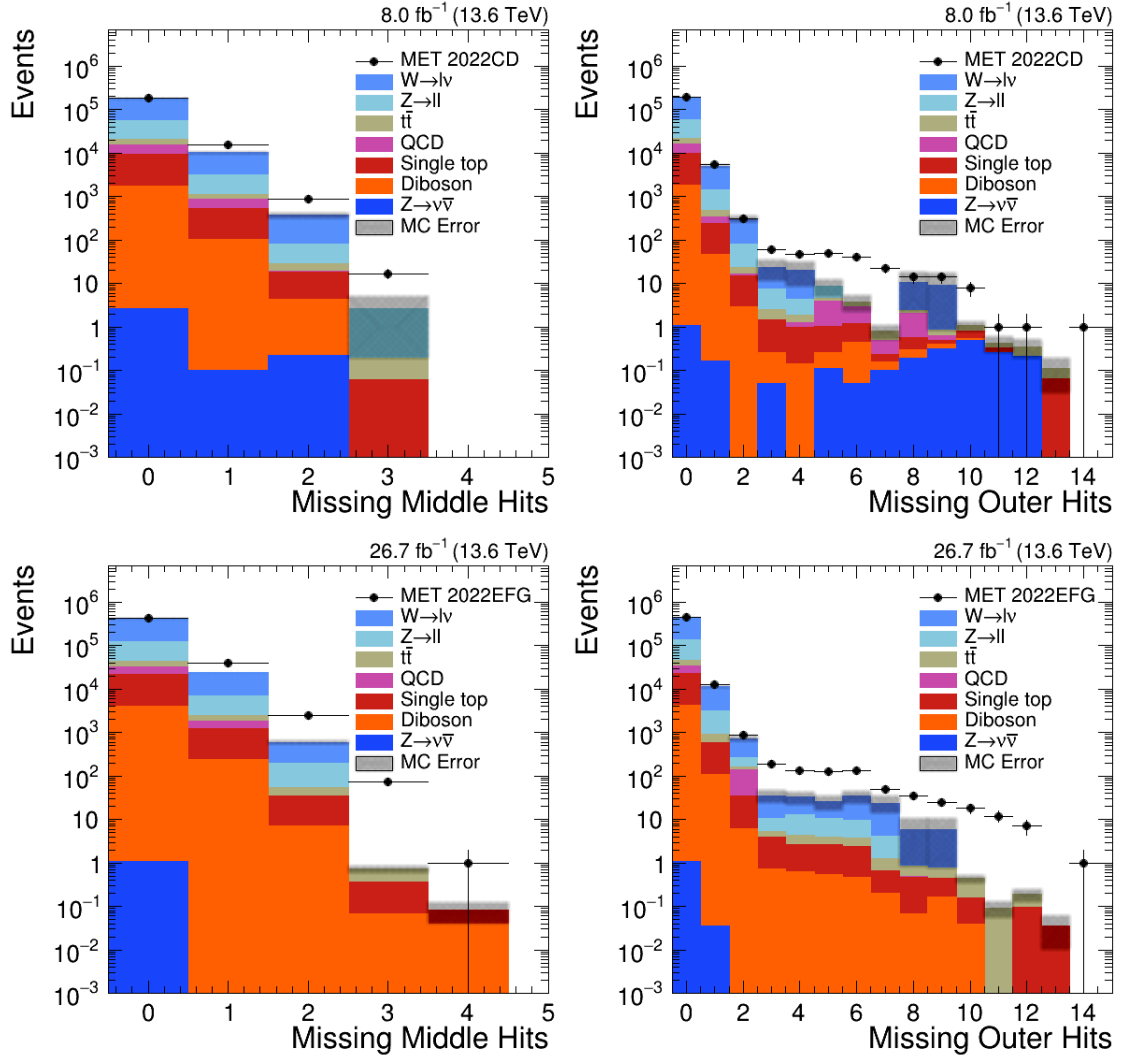


Figure 6.24: Uncorrected distributions of missing middle (left) and outer (right) hits in 2022CD (top) and EFG (bottom). Shown are tracks from the muon control region of collected data and simulated background processes. The $N_{\text{miss}}^{\text{middle}} = 0$ requirement is not applied in the missing middle hits distributions.

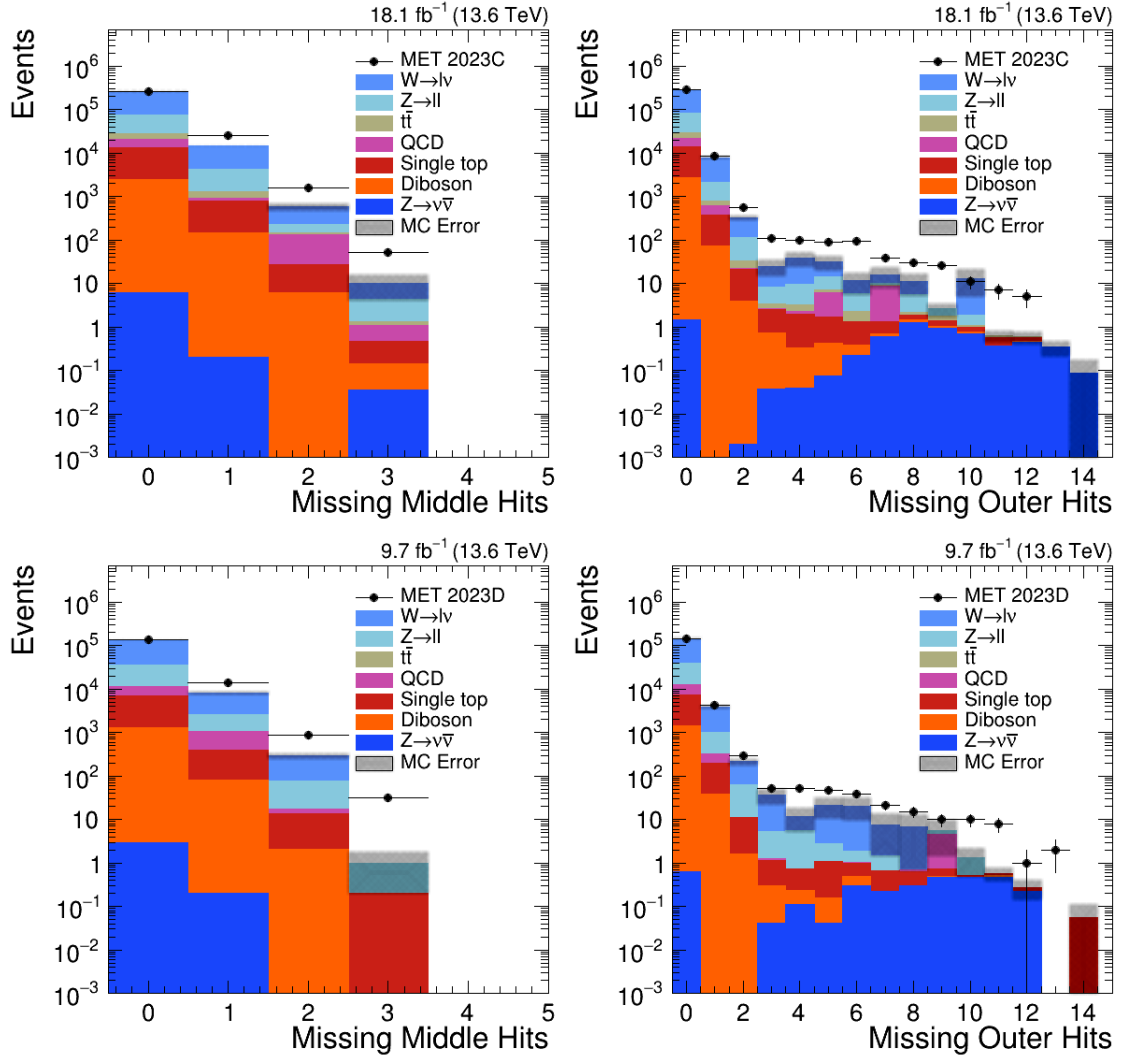


Figure 6.25: Uncorrected distributions of missing middle (left) and outer (right) hits in 2023C (top) and D (bottom). Shown are tracks from the muon control region of collected data and simulated background processes. The $N_{\text{miss}}^{\text{middle}} = 0$ requirement is not applied in the missing middle hits distributions.

The correction process involves determining four probabilities:

- $P_0 \equiv P(\text{missing extra middle hit})$;
- $P_{\text{pre-TOB}} \equiv P(\text{missing extra outer hits})$;
- $P_{\text{TOB}} \equiv P(\text{missing all TOB hits})$;
- $P_{\text{post-TOB}} \equiv P(\text{missing extra outer hits} | \text{missing all TOB hits})$.

P_0 is obtained by fitting the missing middle hits distribution from simulated background events to experimental data without the usual $N_{\text{miss}}^{\text{middle}} = 0$ requirement. A χ^2 minimization method is used to choose the best-fit value.

The remaining three parameters are extracted simultaneously by fitting the missing outer hits distribution with the $N_{\text{miss}}^{\text{middle}} = 0$ criterion applied. A grid search across possible probabilities identifies the combination that minimizes the χ^2 between simulation and data. Values for all the data-taking periods are displayed in Table 6.28. The algorithms used to determine the probabilities are shown in Appendix C.

Table 6.28: Values for the hit removal probabilities obtained by fitting the missing middle and outer hit distributions from simulated background events to those distributions from 2022-2023 experimental data. These values are used to randomly remove hits from the nominal hit patterns of tracks in simulated signal events.

Probability	2022CD	2022EFG	2023C	2023D
P_0	3.390×10^{-3}	5.340×10^{-3}	5.099×10^{-3}	4.828×10^{-3}
P_{TOB}	5.344×10^{-4}	6.638×10^{-4}	8.907×10^{-4}	8.898×10^{-4}
$P_{\text{pre-TOB}}$	2.460×10^{-3}	3.986×10^{-3}	3.092×10^{-3}	4.271×10^{-3}
$P_{\text{post-TOB}}$	0.580	0.602	0.591	0.637

Applying these corrections significantly improves the agreement between the simulation and experimental data, as illustrated in the updated Figures 6.26 and 6.27 for the 2022 and 2023 data sets, respectively. After correction, a systematic uncertainty on the signal selection efficiencies is assigned to account for any residual discrepancies, ensuring that the results maintain robust and reliable estimates.

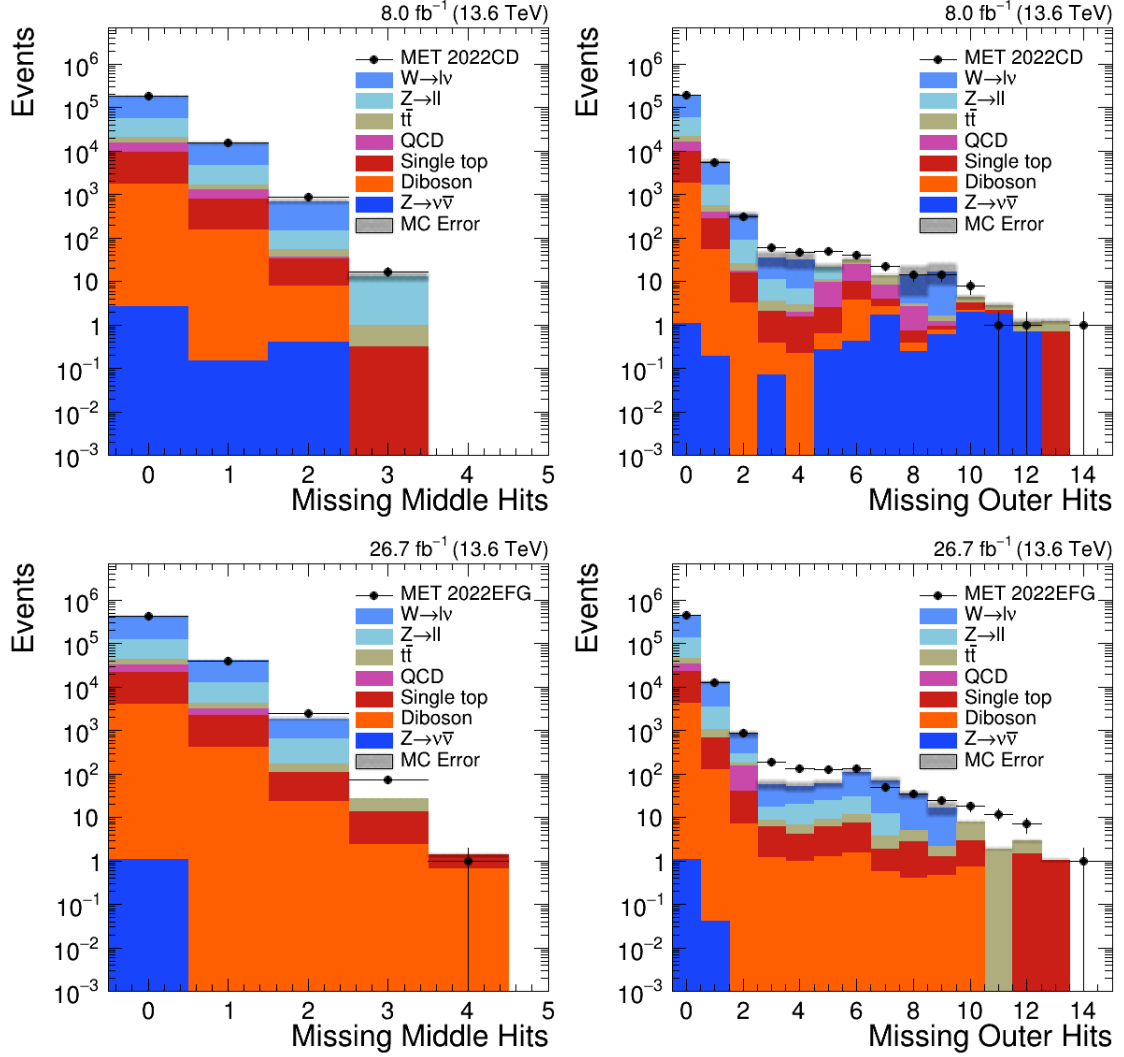


Figure 6.26: Corrected distributions of missing middle (left) and outer (right) hits in 2022CD (top) and EFG (bottom). Shown are tracks from the muon control region of collected data and simulated background processes. The $N_{\text{miss}}^{\text{middle}} = 0$ requirement is not applied in the missing middle hits distributions.

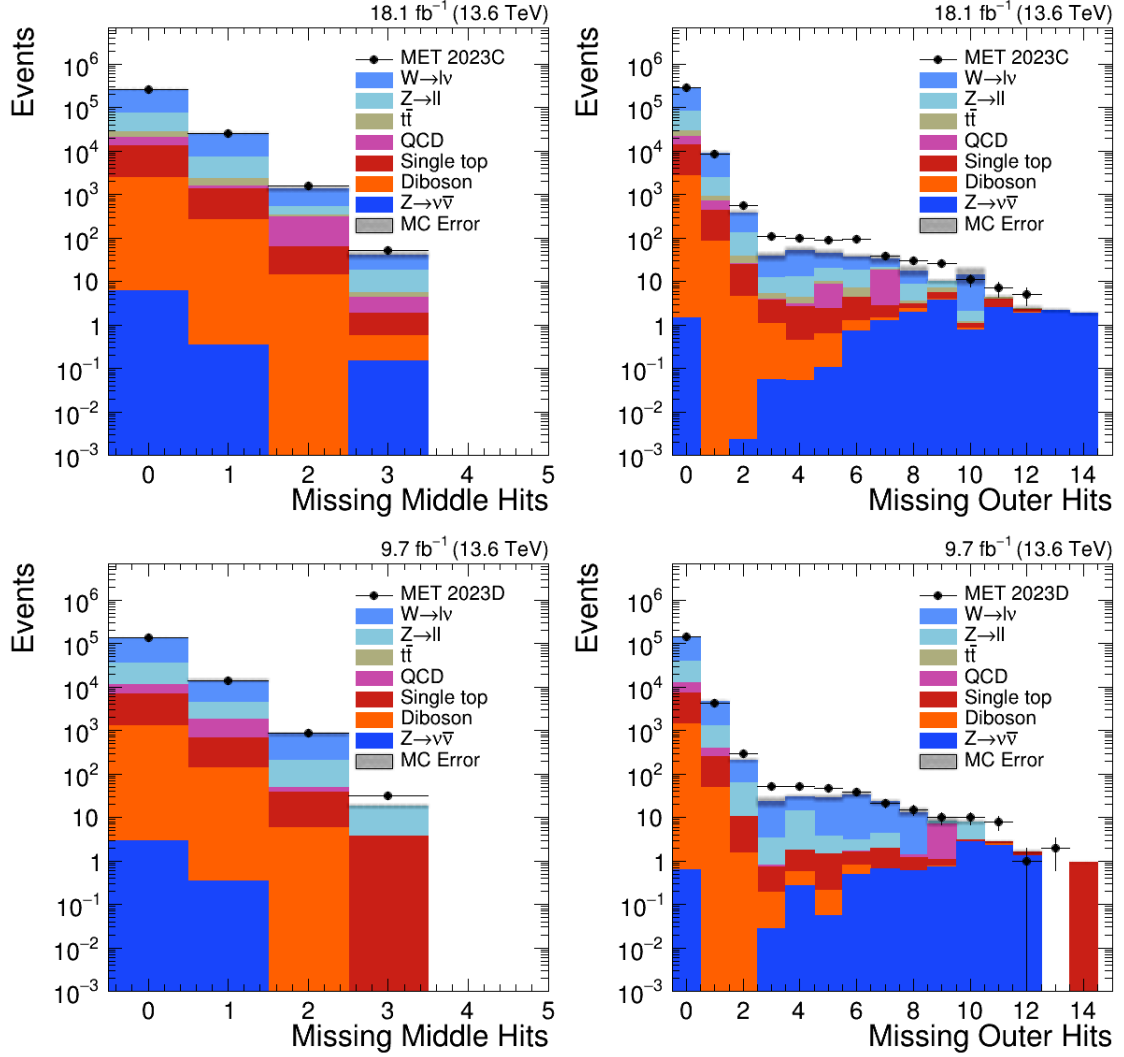


Figure 6.27: Corrected distributions of missing middle (left) and outer (right) hits in 2023C (top) and D (bottom). Shown are tracks from the muon control region of collected data and simulated background processes. The $N_{\text{miss}}^{\text{middle}} = 0$ requirement is not applied in the missing middle hits distributions.

6.5 Systematic Uncertainties

There are several systematic uncertainty sources, which can be divided into two groups: the ones that affect the background estimations and the ones that affect the signal events estimation. Background estimation sources are different for both background sources and essentially depend on the methods used to estimate the expected BG amount. For signal, the uncertainties are related to the scale factors that correct MC $\rightarrow$ data, efficiency, and/or resolution of objects of interest, veto efficiency, and more. The different sources are discussed in more detail below.

6.5.1 Background Estimation Systematics

The charged lepton systematics estimate relies on the assumption that a non-reconstructed lepton contributes with no visible momentum to the $p_T^{\text{miss, no } \mu}$, that is, the expression in Equation 6.4 is not the correct approach. To attribute an uncertainty to it, a scaled-down version (displayed in Equation 6.11) is used to re-estimate P_{offline} and P_{trigger} . The 10 GeV that is subtracted from the lepton p_T , comes from the $E_{\text{calo}} < 10$ GeV requirement for the candidate tracks in the search region. The difference of misreconstructed $\frac{(P_{\text{offline}} P_{\text{trigger}})_{\text{scaled down}}}{(P_{\text{offline}} P_{\text{trigger}})_{\text{nominal}}}$ from one is taken as the uncertainty.

$$\left| \vec{p}_T^{\text{miss, no } \mu} + \frac{p_T^{\text{lepton}} - 10 \text{ GeV}}{p_T^{\text{lepton}}} \vec{p}_T^{\text{lepton}} \right|. \quad (6.11)$$

Tables 6.29 and 6.30 show the estimated uncertainties for the distinct signal region bins in the electron and tau control regions, respectively.

Another source is considered for muons and taus in the categories $n_{\text{layers}} = 4$ and 5. The calculation of P_{offline} and P_{trigger} in these cases is done using the combined category, i.e., $n_{\text{layers}} \geq 4$, given the lack of statistics, which is not ideal. To estimate this uncertainty, the values of P_{offline} and P_{trigger} with $n_{\text{layers}} = 4$ and 5 are compared to the $n_{\text{layers}} \geq 4$ category using events from the electron control region. The opposite of the difference between the distinct values are set as one-sided uncertainties in the muons and taus estimates. Table 6.31 shows the calculated results.

The fake track systematic uncertainty comes from a possible dependence on the probability of having a fake track in the distinct control regions, and an uncertainty

Table 6.29: Estimated P_{offline} and P_{trigger} using the nominal and scaled down $|\vec{p}_T^{\text{miss, no } \mu} + \vec{p}_T^{\text{lepton}}|$ distributions with events from the single electron control region. The calculated systematic uncertainty is shown in the last column.

run period	n_{layers}	nominal		scaled down		systematic uncertainty
		P_{offline}	P_{trigger}	P_{offline}	P_{trigger}	
2022CD	4	0.644 ± 0.019	0.370 ± 0.048	0.566 ± 0.018	0.371 ± 0.048	11.8%
	5	0.655 ± 0.012	0.425 ± 0.033	0.583 ± 0.011	0.409 ± 0.031	14.5%
	≥ 6	0.724 ± 0.003	0.402 ± 0.006	0.654 ± 0.002	0.388 ± 0.006	12.8%
2022EFG	4	0.635 ± 0.012	0.476 ± 0.034	0.563 ± 0.011	0.465 ± 0.034	13.5%
	5	0.645 ± 0.007	0.500 ± 0.021	0.574 ± 0.006	0.485 ± 0.020	13.8%
	≥ 6	0.712 ± 0.001	0.509 ± 0.004	0.642 ± 0.001	0.493 ± 0.004	12.6%
2023C	4	0.634 ± 0.015	0.501 ± 0.045	0.572 ± 0.014	0.482 ± 0.043	13.2%
	5	0.657 ± 0.009	0.491 ± 0.024	0.589 ± 0.008	0.474 ± 0.024	13.6%
	≥ 6	0.710 ± 0.002	0.531 ± 0.005	0.645 ± 0.002	0.514 ± 0.005	12.1%
2023D	4	0.637 ± 0.022	0.428 ± 0.062	0.580 ± 0.021	0.412 ± 0.059	12.3%
	5	0.651 ± 0.013	0.504 ± 0.041	0.587 ± 0.012	0.488 ± 0.039	12.8%
	≥ 6	0.698 ± 0.003	0.532 ± 0.008	0.635 ± 0.002	0.515 ± 0.008	12.1%

Table 6.30: Estimated P_{offline} and P_{trigger} using the nominal and scaled down $|\vec{p}_T^{\text{miss, no } \mu} + \vec{p}_T^{\text{lepton}}|$ distributions with events from the single tau control region. The calculated systematic uncertainty is shown in the last column. For $n_{\text{layers}} = 4$ and 5, there was not enough statistics, and the uncertainty was estimated using the combined category.

run period	n_{layers}	nominal		scaled down		systematic uncertainty
		P_{offline}	P_{trigger}	P_{offline}	P_{trigger}	
2022CD	4	-	-	-	-	3.1%
	5	-	-	-	-	3.1%
	≥ 6	0.208 ± 0.031	0.449 ± 0.101	0.208 ± 0.031	0.435 ± 0.099	3.1%
2022EFG	4	-	-	-	-	0.3%
	5	-	-	-	-	0.3%
	≥ 6	0.235 ± 0.018	0.543 ± 0.059	0.238 ± 0.018	0.534 ± 0.058	0.3%
2023C	4	-	-	-	-	2.1%
	5	-	-	-	-	2.1%
	≥ 6	0.257 ± 0.025	0.580 ± 0.080	0.262 ± 0.025	0.556 ± 0.076	2.1%
2023D	4	-	-	-	-	3.1%
	5	-	-	-	-	3.1%
	≥ 6	0.262 ± 0.034	0.580 ± 0.106	0.266 ± 0.034	0.555 ± 0.101	3.1%

Table 6.31: P_{offline} and P_{trigger} estimated in the single electron control region in categories $n_{\text{layers}} = 4$, $n_{\text{layers}} = 5$, and the combined case with $n_{\text{layers}} \geq 4$.

run period	n_{layers}	electron background	
		P_{offline}	P_{trigger}
2022CD	4	0.644 ± 0.019 (-10.68%)	0.370 ± 0.048 (-8.64%)
	5	0.655 ± 0.012 (-9.15%)	0.425 ± 0.033 ($+4.94\%$)
	combined	0.721 ± 0.002	0.405 ± 0.006
2022EFG	4	0.635 ± 0.012 (-10.45%)	0.476 ± 0.034 (-6.48%)
	5	0.645 ± 0.007 (-8.90%)	0.500 ± 0.021 (-1.77%)
	combined	0.708 ± 0.001	0.509 ± 0.004
2023C	4	0.634 ± 0.015 (-10.45%)	0.501 ± 0.045 (-5.47%)
	5	0.651 ± 0.013 (-8.05%)	0.491 ± 0.024 (-7.36%)
	combined	0.708 ± 0.002	0.530 ± 0.005
2023D	4	0.637 ± 0.022 (-8.48%)	0.428 ± 0.062 (-19.55%)
	5	0.651 ± 0.013 (-6.47%)	0.504 ± 0.041 (-5.26%)
	combined	0.696 ± 0.002	0.532 ± 0.008

in the transfer factor ζ . For the first source, the difference between the distinct control regions is assigned as an uncertainty, and in the second, the uncertainty is estimated by fluctuating the Gaussian fit parameter up and down by 1σ , and the transfer factor is re-evaluated. Table 6.32 shows the estimated uncertainties for the different sources and signal region bins.

6.5.2 Signal Selection Systematics

Most of the signal systematics calculated for the signal are related to corrections from MC to data. All the corrections applied above get their systematics related to the method used, and there are also uncertainties associated with the relevant objects' resolution/efficiency, such as jet energy, $p_{\text{T}}^{\text{miss}}$, E_{calo} , lepton veto, and track reconstruction. Also, an uncertainty in the estimation of the integrated luminosity of the collected data is taken into account. For 2022, this uncertainty is estimated as 1.4% [245], and for 2023 it is estimated as 1.3% [246]. These calculations are performed by the dedicated CMS group.

Table 6.32: Estimated systematic uncertainties on the fake track background estimate.

run period	n_{layers}	uncertainty source		total
		control region	transfer factor	
2022CD	4	6.6%	76.0%	76.3%
	5	33.9%	76.0%	83.2%
	≥ 6	100%	76.0%	125.6%
2022EFG	4	63.8%	46.0%	78.7%
	5	52.1%	46.0%	69.5%
	≥ 6	12.5%	46.0%	47.7%
2023C	4	1.6%	182.2%	182.2%
	5	12.4%	182.2%	182.6%
	≥ 6	166.7%	182.2%	247.0%
2023D	4	6.6%	113.8%	114.0%
	5	34.7%	113.8%	119.0%
	≥ 6	200.0%	113.8%	230.1%

Trigger Efficiency Correction

The uncertainty associated to the trigger efficiency comes from two sources: the limited amount of data used to extract the scale factors, and the online requirement on the number of hits of the isolated track in the `*IsoTrk50*` paths, $n_{\text{hits}} \geq 5$, which impacts the trigger efficiency for tracks with $n_{\text{layers}} = 4$ or 5. To extract the systematics for the first source, the efficiency calculated using MC and data is varied up and down by one standard deviation, and the scale factors are recalculated. The difference in the amount of observed signal events from the central value is assigned as the uncertainty. The second source is estimated as the ratio of the efficiencies in $n_{\text{layers}} = 4$ or 5 with the $n_{\text{layers}} \geq 6$ case (shown in Figure 6.28) convolved with the $p_{\text{T}}^{\text{miss, no } \mu}$, to estimate the difference in selected signal events, for every chargino mass/lifetime.

The combined systematic uncertainty on the trigger efficiency, averaged over all chargino masses and lifetimes, is displayed in Table 6.33 for all data-taking periods and n_{layers} categories. The 2022 period also takes into account the source mentioned in 4.3, where during 2022C an issue with the jet energy calibrations at the L1T caused a decrease in efficiency in the HLT $p_{\text{T}}^{\text{miss}}$ paths. This source accounts for 0.6% of uncertainty that is summed in quadrature, given that, conservatively,

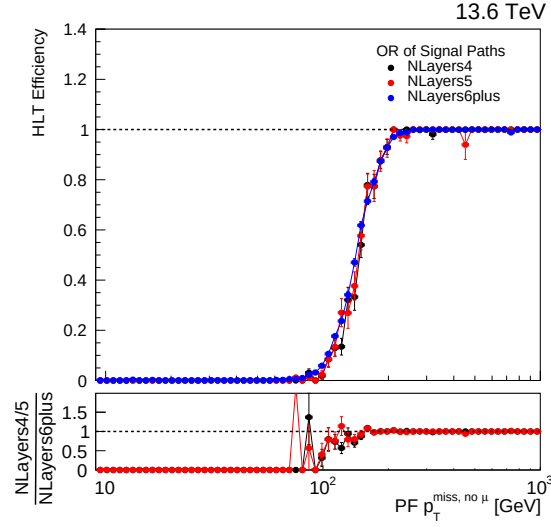


Figure 6.28: Efficiency of p_T^{miss} triggers estimated with simulated signal events with a chargino mass of 700 GeV. Each category is shown in the image: $n_{\text{layers}} = 4$ (black), $n_{\text{layers}} = 5$ (red) and $n_{\text{layers}} = 6$ or more (blue). In the subplot, the ratio between the $n_{\text{layers}} = 4$ (black) and $n_{\text{layers}} = 5$ (red) with $n_{\text{layers}} = 6$ or more is being plotted. Every chargino lifetime is considered, given that the chargino decay length does not affect the $p_T^{\text{miss, no } \mu}$ of each event. Period 2022EE is shown.

the issue reduced the efficiency of these paths by $\sim 10\%$, and it affected $\sim 6\%$ of the collected data.

Pileup

Systematic uncertainty over PU is needed due to the assumption of the minimum bias cross section, since it can be different from that of the data. The nominal value used to extract the PU distributions in 2022 and 2023 is 69200 mb, with an uncertainty of 4.6%. The uncertainty associated with this assumption is obtained by varying the nominal value by $\pm 1\sigma$, and extracting new PU corrections to the signal, where the varied distributions are shown in Figure 6.29. The difference in the signal yield is assigned as the uncertainty and is 2.9–6.4% on average.

ISR

Similarly to the above, the ISR assumption on the production mechanism for pairs of LLPs is not known, so the scale factors associated with it are re-estimated, varying the central values up and down by one standard deviation, and the new SFs are used in signal MC. The deviation from the central value is assigned as an

Table 6.33: Systematic uncertainties estimated for the trigger efficiency, the efficiency turn-on curve and the total, for each of the data taking periods and n_{layers} categories.

run period	n_{layers}	systematic uncertainty			Total
		Efficiency	Turn-on	2022C Issue	
2022	4	0.22%	0.76%	0.6%	0.99%
	5	0.19%	0.40%	0.6%	0.75%
	≥ 6	0.21%	—	0.6%	0.64%
2022EE	4	0.20%	0.48%	—	0.52%
	5	0.19%	0.44%	—	0.48%
	≥ 6	0.23%	—	—	0.23%
2023	4	0.49%	0.71%	—	0.86%
	5	0.51%	0.56%	—	0.76%
	≥ 6	0.51%	—	—	0.51%
2023BPix	4	0.46%	0.71%	—	0.85%
	5	0.50%	0.65%	—	0.82%
	≥ 6	0.50%	—	—	0.50%

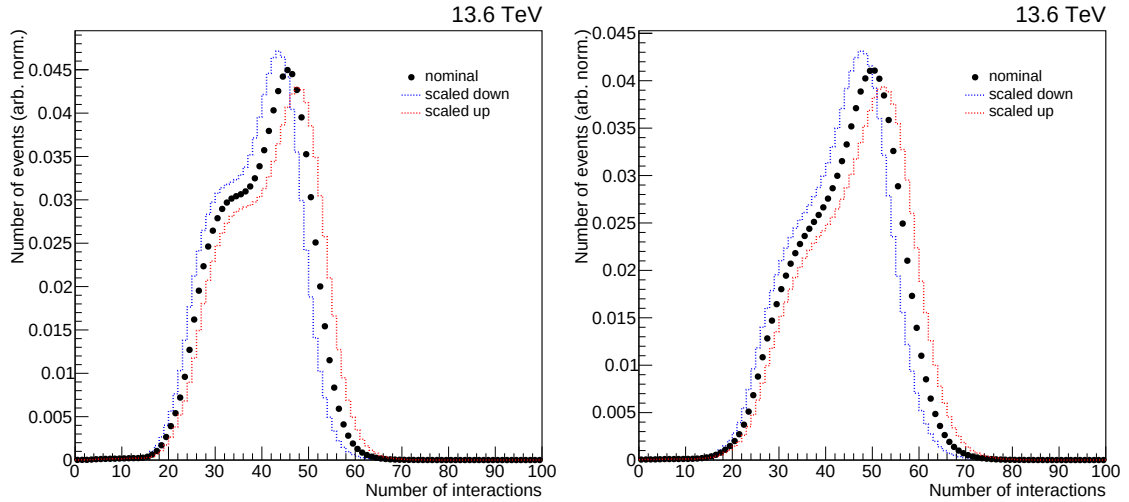


Figure 6.29: Nominal (black circles) and scaled up (red dotted line) and down (blue dotted line) pileup distributions for 2022 (left) and 2023 (right) data sets.

uncertainty, where the average value for this uncertainty is 6.6–7.1%.

Missing Middle and Outer Hits

The uncertainty related to the modeling of missing inner and middle hits in the simulation is assessed using three control regions. The first is the muon control region, where the muon veto (defined in Table 6.15) is removed, and the second and third combine events from $Z \rightarrow \mu\mu + \tau_h$ and $Z \rightarrow ee + \tau_h$ selections, defined by the $Z \rightarrow \mu\mu$ and $Z \rightarrow ee$, while also requiring that the track passes the candidate track selection with the tau veto (defined in Table 6.15) removed. These additional regions provide samples more similar to the search region but still dominated by background processes.

The $Z + \tau_h$ control regions are introduced because the presence of nearby reconstructed muons can lead to additional track fitting iterations, potentially improving hit-finding efficiency. As this effect might differ between simulated and collected data, the $Z + \tau_h$ regions allow a more accurate study of these discrepancies. These selections evaluate the efficiencies for meeting the $N_{\text{miss}}^{\text{inner}} = 0$ and $N_{\text{miss}}^{\text{middle}} = 0$ criteria without applying the requirement initially.

The systematic uncertainty is calculated by comparing efficiencies between data and simulation, with the larger uncertainty (between the muon and $Z + \tau_h$ regions) chosen as the systematic assigned to the signal. In the muon control region, the systematic is derived across all track categories with $n_{\text{layers}} \geq 6$, while in the $Z + \tau_h$ regions, uncertainties are evaluated separately for different categories. Table 6.34 lists the derived uncertainties, and Figure 6.30 shows a comparison of data to simulation for the relevant distributions.

The modeling of missing outer hits is treated separately, focusing specifically on distinguishing between true and accidental missing outer hits. True missing outer hits originate from particles failing to reach the tracker's outer layers, as expected from signal events. Accidental missing outer hits, however, arise from detector inefficiencies or reconstruction errors. Since muon tracks dominate the muon control region and rarely exhibit true missing outer hits, the observed distributions mainly represent accidental hits.

Given that true missing outer hits are well-modeled, the uncertainty estimation

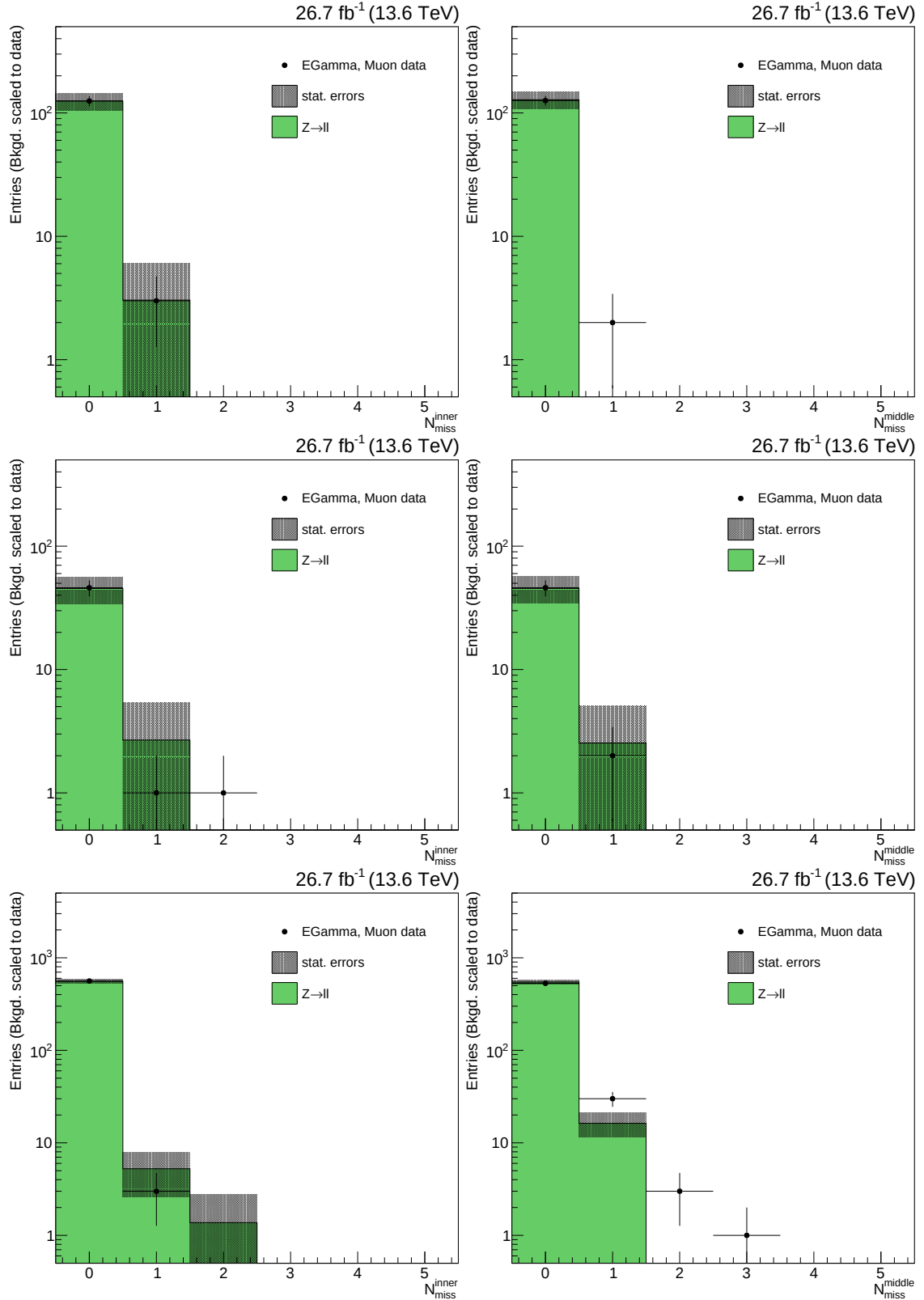


Figure 6.30: Number of missing inner (left) and middle (right) hits for tracks from the $Z + \tau_h$ control regions, without the $N_{\text{miss}}^{\text{inner}} = 0$ and $N_{\text{miss}}^{\text{middle}} = 0$ requirements. Shown are the $n_{\text{layers}} = 4$ (top), $n_{\text{layers}} = 5$ (middle), and $n_{\text{layers}} \geq 6$ (bottom) categories for the 2022EFG data set.

Table 6.34: Systematic uncertainties estimated for the missing inner and middle hits selections with events in each of the data taking periods, n_{layers} categories and control regions.

run period	n_{layers}	systematic uncertainty			
		inner		middle	
		μ	$Z + \tau_h$	μ	$Z + \tau_h$
2022	4	0.28%	$\sim 0.00\%$	2.81%	2.86%
	5	0.28%	$\sim 0.00\%$	2.81%	1.13%
	≥ 6	0.28%	0.89%	2.81%	2.05%
2022EE	4	$\sim 0.00\%$	0.03%	3.83%	1.59%
	5	$\sim 0.00\%$	1.48%	3.83%	1.17%
	≥ 6	$\sim 0.00\%$	0.65%	3.83%	3.35%
2023	4	0.15%	1.78%	4.20%	5.88%
	5	0.15%	$\sim 0.00\%$	4.20%	2.08%
	≥ 6	0.15%	0.57%	4.20%	0.12%
2023BPix	4	0.30%	2.02%	4.21%	$\sim 0.00\%$
	5	0.30%	4.17%	4.21%	4.17%
	≥ 6	0.30%	0.5%	4.21%	0.34%

focuses only on the accidental component. The signal yield depends on the efficiency for a track to have at least three missing outer hits, as shown below:

$$\varepsilon^{\geq 3} = \varepsilon_{\text{true}}^{\geq 3} + \varepsilon_{\text{true}}^{\geq 2} \cdot \varepsilon_{\text{acc.}}^{\geq 1} + \varepsilon_{\text{true}}^{\geq 1} \cdot \varepsilon_{\text{acc.}}^{\geq 2} + \varepsilon_{\text{true}}^{\geq 0} \cdot \varepsilon_{\text{acc.}}^{\geq 3}, \quad (6.12)$$

where $\varepsilon_{\text{true}}^p$ ($\varepsilon_{\text{acc.}}^p$) are the efficiencies for tracks to have p true (accidental) missing outer hits. These efficiencies are estimated separately for simulated signal samples and muon control region data.

The systematic uncertainty is assigned based on the relative difference in the efficiency between experimental and simulated data. The resulting uncertainties are often zero for many signal scenarios with $n_{\text{layers}} = 4$ and 5, and peak at 0.2% for the $n_{\text{layers}} \geq 6$ category.

Jet Energy Corrections

Jet energy corrections (JECs) are applied to the events to remove PU contributions, make the p_T and η distributions more uniform, and to correct small MC to

data differences, which also carries a systematic uncertainty with it. The uncertainty on the energy scale is estimated by varying the p_T of the jets in the event by 1σ on the cumulative jet energy corrections, and the difference of the varied signal yield to the central value is assigned as the systematics. The uncertainty on the jets' energy resolution (JER) uses two distinct methods: the scaling method, which includes the following factor on the reconstructed jet p_T :

$$c_{\text{JER}} = 1 + (s_{\text{JER}} - 1) \frac{p_{T,\text{reco}} - p_{T,\text{gen}}}{p_{T,\text{reco}}}, \quad (6.13)$$

where s_{JER} is a quantity measured by the dedicated CMS group, obtained as the fraction of simulated and collected jets p_T resolution; the second method is the stochastic smearing, in which a random factor is used to scale the reconstructed jets p_T , using the s_{JER} :

$$c_{\text{JER}} = 1 + N(0, \sigma_{\text{JER}}) \sqrt{\max(s_{\text{JER}}^2 - 1, 0)}, \quad (6.14)$$

where $N(0, \sigma_{\text{JER}})$ is a standard Gaussian distribution of mean 0 and variance equal to the square of the relative p_T resolution measured by the dedicated CMS group. To define a reconstructed jet as a well-matched jet, it has to have the following properties when compared to a generated jet:

$$\Delta R < \frac{R}{2} \text{ and } |p_{T,\text{reco}} - p_{T,\text{gen}}| < 3\sigma_{\text{JEC}} p_{T,\text{reco}}, \quad (6.15)$$

with $R = 0.4$ jets' anti- k_T cone parameter. The uncertainty is assigned as the difference in signal yield when using both methods to vary jets p_T , and is 0.4–4.6% on average.

p_T^{miss}

Given that p_T^{miss} is one of the most important objects in the analysis and is subject to several uncertainties related to the sum of the p_T of the visible objects, its systematic uncertainty is determined by the variation of the p_T of all visible objects according to each object's energy resolution, and the p_T^{miss} of the event is recalculated. The average difference for each of the varied objects p_T is displayed in Table 6.35. The relative change in signal yield is assigned as this systematic.

Table 6.35: p_T^{miss} systematic uncertainty estimated from the variation due to different final state objects. The values are averaged over all charginos masses and lifetimes. The variation of the electron energy scale is performed, but the change in p_T^{miss} is negligible.

type	average sys. uncertainty			
	2022	2022EE	2023	2023BPix
jet resolution, energy scale	0.3%	0.4%	0.2%	0.3%
tau energy scale	0.2%	0.1%	0.1%	0.2%
photon energy scale	1.5%	1.7%	1.4%	1.7%
unclustered energy scale	0.3%	0.2%	0.5%	0.4%

E_{calo}

On the same note, the calorimeter energy associated with the candidate tracks is estimated using the energy of the closest calorimeter jet to it, and its systematic uncertainty is determined as the difference in the variable when comparing data with simulation. The variable distributions are extracted from the $Z \rightarrow \mu\mu$ control region for tracks with $n_{\text{layers}} \leq 4$, since there is an excess of fake tracks, and the energy on the calorimeter is expected to be uniformly distributed. The difference in the efficiency of the E_{calo} selection when comparing data with MC is set as an uncertainty, and the values for the distinct data taking periods are shown in Table 6.36. It is possible to notice that the systematic uncertainty for both 2023 periods is very large. This is related to the very distinct PU distribution when comparing MC with data in 2023 (see Figure 6.22), and the lack of a PU subtraction technique in the estimation of E_{calo} with the CaloJets.

Table 6.36: Calculated efficiency of the $E_{\text{calo}} < 10 \text{ GeV}$ selection for tracks with $n_{\text{layers}} = 4$ from the $Z \rightarrow \mu\mu$ control region in collected data and simulation. The estimated systematic uncertainty is shown in the rightmost column.

run period	eff. of $E_{\text{calo}} < 10 \text{ GeV}$		systematic uncertainty
	data	simulation	
2022	$(89.9 \pm 1.3)\%$	$(87.8 \pm 2.9)\%$	2.3%
2022EE	$(86.8 \pm 0.7)\%$	$(89.8 \pm 1.5)\%$	3.5%
2023	$(86.7 \pm 0.9)\%$	$(70.5 \pm 1.4)\%$	18.8%
2023BPix	$(86.1 \pm 1.4)\%$	$(68.3 \pm 1.8)\%$	20.7%

Lepton Veto

Another relevant point in the events' selection is the lepton veto, that is, when the isolated track is required not to be consistent with reconstructed electrons and muons. An uncertainty is assigned to it, based on the scale factor extracted from the efficiency of this requirement when comparing data with MC. Also, since the dedicated CMS groups do not provide the scale factors for the working point used in this analysis, a normalization with respect to the loosest approved working point is used. The expression for the scale factor is the following:

$$SF = (\text{centrally measured loose ID SF}) \cdot \frac{\epsilon_{\text{veto}}^{\text{data}}}{\epsilon_{\text{loose}}^{\text{data}}} \cdot \frac{\epsilon_{\text{loose}}^{\text{MC}}}{\epsilon_{\text{veto}}^{\text{MC}}}, \quad (6.16)$$

where veto stands for the working point used in this analysis, and loose, to the loosest point approved centrally by the CMS experts. The MC efficiencies are estimated in the signal samples search selection, and the data over the T&P samples defined in Section 6.2.2, where the electron ϵ is determined in the muon control region, and the muon ϵ in the electron control region to measure each value in regions where the object vetoed is not abundant to guarantee the purity of tracks.

Tracks Reconstruction

Finally, the last uncertainty comes from the tracks' reconstruction efficiency, which is measured by the dedicated CMS group. The difference in the efficiency when comparing data to Monte Carlo (as shown in Figure 6.31) is assigned as a systematic uncertainty, and is 0.7% for both 2022 periods and 2023, and 2.0% for 2023BPix.

Summary

Tables 6.37 and 6.38 for the wino-like LSP case and Tables 6.39 and 6.40 for the higgsino-like LSP contain the summary of every systematic uncertainty source estimation. The values displayed in the tables are the average results over all masses (100–1200 GeV for wino-like and 100–1000 GeV for higgsino-like) and lifetimes (from 0.2 to 10000 cm of $c\tau$).

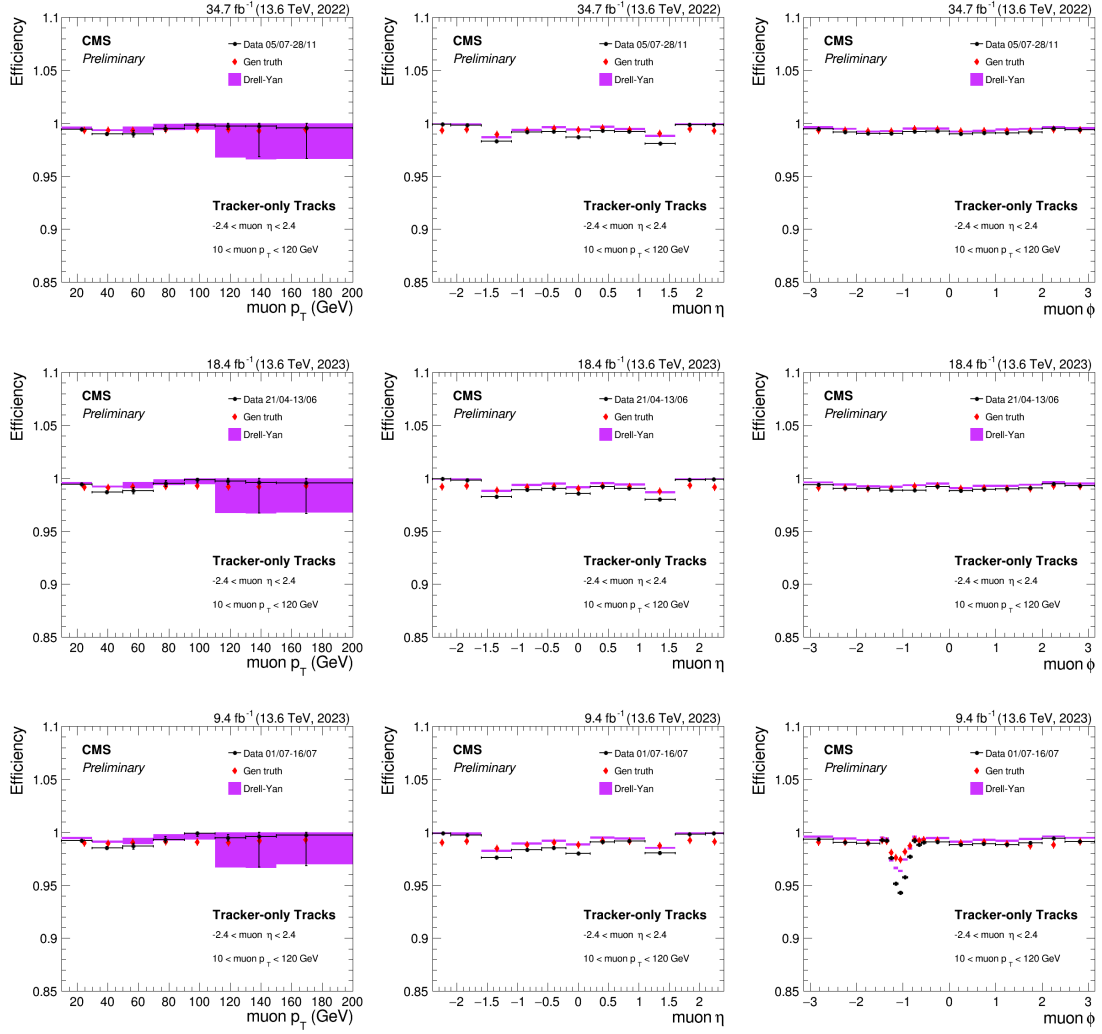


Figure 6.31: Tracking efficiency measured with a muon tag-and-probe study by the dedicated CMS group. The comparison between collected and simulated data is performed as a function of muon p_T (left), η (middle), and ϕ (right). Shown are comparisons with data from 2022 (top), 2023 (middle), and 2023BPix (bottom). Source: [243].

Table 6.37: Summary of systematic uncertainties taken from 2022 simulation. The values are the average of the results over all produced wino-like samples. The total listed on the last line is simply the sum in quadrature of each of the individual uncertainties.

source of uncertainty	run period	average value		
		$n_{\text{layers}} = 4$	$n_{\text{layers}} = 5$	$n_{\text{layers}} \geq 6$
pileup	2022	5.3%	4.9%	3.6%
	2022EE	3.6%	3.9%	3.4%
ISR	2022	6.8%	6.8%	6.7%
	2022EE	6.6%	6.7%	6.7%
trigger efficiency	2022	1.0%	0.8%	0.6%
	2022EE	0.5%	0.5%	0.2%
jet energy scale	2022	2.0%	2.5%	2.3%
	2022EE	0.8%	1.0%	1.9%
jet energy resolution	2022	1.6%	2.0%	2.0%
	2022EE	0.5%	0.6%	2.0%
$p_{\text{T}}^{\text{miss}}$	2022	0.6%	0.3%	0.4%
	2022EE	0.5%	0.5%	0.4%
E_{calo}	2022	2.3%	2.3%	2.3%
	2022EE	3.5%	3.5%	3.5%
missing inner hits	2022	0.3%	0.3%	0.9%
	2022EE	$\sim 0\%$	1.5%	0.7%
missing middle hits	2022	2.9%	2.8%	2.8%
	2022EE	3.8%	3.8%	3.8%
missing outer hits	2022	$\sim 0\%$	$\sim 0\%$	0.1%
	2022EE	$\sim 0\%$	$\sim 0\%$	0.2%
lepton veto scale factor	2022	0.02%	0.01%	0.10%
	2022EE	0.05%	0.02%	0.01%
track reconstruction efficiency	2022	0.7%	0.7%	0.7%
	2022EE	0.7%	0.7%	0.7%
total	2022	9.4%	9.3%	8.6%
	2022EE	9.2%	9.5%	9.6%

Table 6.38: Summary of systematic uncertainties taken from 2023 simulation. The values are the average of the results over all produced wino-like samples. The total listed on the last line is simply the sum in quadrature of each of the individual uncertainties.

source of uncertainty	run period	average value		
		$n_{\text{layers}} = 4$	$n_{\text{layers}} = 5$	$n_{\text{layers}} \geq 6$
pileup	2023	4.2%	5.2%	3.8%
	2023BPix	4.4%	3.7%	3.9%
ISR	2023	6.9%	7.0%	7.1%
	2023BPix	7.0%	7.1%	7.1%
trigger efficiency	2023	0.9%	0.8%	0.5%
	2023BPix	0.9%	0.8%	0.5%
jet energy scale	2023	4.8%	3.1%	3.1%
	2023BPix	0.8%	0.7%	1.4%
jet energy resolution	2023	4.6%	3.0%	2.8%
	2023BPix	0.4%	0.5%	1.3%
$p_{\text{T}}^{\text{miss}}$	2023	0.4%	0.4%	0.4%
	2023BPix	0.5%	0.5%	0.5%
E_{calo}	2023	18.8%	18.8%	18.8%
	2023BPix	20.7%	20.7%	20.7%
missing inner hits	2023	1.8%	0.2%	0.6%
	2023BPix	2.0%	4.2%	0.5%
missing middle hits	2023	5.9%	4.2%	4.2%
	2023BPix	4.2%	4.2%	4.2%
missing outer hits	2023	$\sim 0\%$	$\sim 0\%$	0.2%
	2023BPix	$\sim 0\%$	$\sim 0\%$	0.1%
lepton veto scale factor	2023	0.03%	0.03%	0.02%
	2023BPix	0.21%	0.03%	0.02%
track reconstruction efficiency	2023	0.7%	0.7%	0.7%
	2023BPix	2.0%	2.0%	2.0%
total	2023	21.5%	21.2%	20.9%
	2023BPix	22.4%	22.3%	22.4%

Table 6.39: Summary of systematic uncertainties taken from 2022 simulation. The values are the average of the results over all produced higgsino-like samples. The total listed on the last line is simply the sum in quadrature of each of the individual uncertainties.

source of uncertainty	run period	average value		
		$n_{\text{layers}} = 4$	$n_{\text{layers}} = 5$	$n_{\text{layers}} \geq 6$
pileup	2022	4.8%	4.5%	3.1%
	2022EE	5.0%	4.6%	4.0%
ISR	2022	6.8%	6.7%	6.7%
	2022EE	6.9%	6.7%	6.7%
trigger efficiency	2022	0.9%	0.8%	0.6%
	2022EE	0.8%	0.6%	0.2%
jet energy scale	2022	1.9%	2.4%	2.1%
	2022EE	2.2%	1.5%	2.5%
jet energy resolution	2022	1.7%	2.0%	1.4%
	2022EE	1.7%	1.2%	2.1%
$p_{\text{T}}^{\text{miss}}$	2022	0.5%	0.4%	0.5%
	2022EE	0.4%	0.5%	0.4%
E_{calo}	2022	2.3%	2.3%	2.3%
	2022EE	3.5%	3.5%	3.5%
missing inner hits	2022	0.3%	0.3%	0.9%
	2022EE	$\sim 0\%$	1.5%	0.7%
missing middle hits	2022	2.9%	2.8%	2.8%
	2022EE	3.8%	3.8%	3.8%
missing outer hits	2022	$\sim 0\%$	$\sim 0\%$	0.1%
	2022EE	$\sim 0\%$	$\sim 0\%$	0.2%
lepton veto scale factor	2022	0.01%	0.01%	0.10%
	2022EE	0.04%	0.02%	0.01%
track reconstruction efficiency	2022	0.7%	0.7%	0.7%
	2022EE	0.7%	0.7%	0.7%
total	2022	9.5%	9.5%	8.7%
	2022EE	10.4%	10.0%	10.0%

Table 6.40: Summary of systematic uncertainties taken from 2023 simulation. The values are the average of the results over all produced higgsino-like samples. The total listed on the last line is simply the sum in quadrature of each of the individual uncertainties.

source of uncertainty	run period	average value		
		$n_{\text{layers}} = 4$	$n_{\text{layers}} = 5$	$n_{\text{layers}} \geq 6$
pileup	2023	4.5%	4.1%	2.9%
	2023BPix	6.4%	3.7%	3.4%
ISR	2023	6.9%	7.0%	6.8%
	2023BPix	7.0%	7.0%	6.8%
trigger efficiency	2023	1.5%	0.9%	0.5%
	2023BPix	1.1%	0.9%	0.5%
jet energy scale	2023	1.6%	1.5%	3.1%
	2023BPix	1.3%	1.2%	3.0%
jet energy resolution	2023	1.2%	1.3%	3.1%
	2023BPix	1.1%	0.8%	2.4%
$p_{\text{T}}^{\text{miss}}$	2023	0.6%	0.3%	0.6%
	2023BPix	0.3%	0.8%	0.5%
E_{calo}	2023	18.8%	18.8%	18.8%
	2023BPix	20.7%	20.7%	20.7%
missing inner hits	2023	1.8%	0.2%	0.6%
	2023BPix	2.0%	4.2%	0.5%
missing middle hits	2023	5.9%	4.2%	4.2%
	2023BPix	4.2%	4.2%	4.2%
missing outer hits	2023	$\sim 0\%$	$\sim 0\%$	0.2%
	2023BPix	$\sim 0\%$	$\sim 0\%$	0.2%
lepton veto scale factor	2023	0.03%	0.03%	0.02%
	2023BPix	0.03%	0.04%	0.02%
track reconstruction efficiency	2023	0.7%	0.7%	0.7%
	2023BPix	2.0%	2.0%	2.0%
total	2023	21.6%	21.0%	21.1%
	2023BPix	23.4%	23.1%	22.9%

6.6 Results

The signal region data are still blinded at the time of this writing; expected limits can be derived using the Asimov dataset under the BG-only hypothesis. With the estimated number of background events, it is possible to set expected 95% CL_s upper limits on the production cross section of electroweakinos production in the context of the AMSB model. Recall from Chapter 4 that this production arises via the processes $pp \rightarrow \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp$ and $pp \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^\pm$, occurring in an approximate ratio of 1 : 2. Upper limits on the total production cross section are estimated across a grid of chargino masses and lifetimes.

The computation of these limits is done with the modified frequentist method, often referred to as CL_s [247, 248], specifically adopting the LHC-style CL_s method [249]. This technique utilizes a test statistic based on a profile likelihood ratio [250], with nuisance parameters handled in a frequentist framework. The systematic uncertainties related to the integrated luminosity and the signal selection efficiency are constrained using log-normal distributions. Two distinct categories of nuisance parameters address uncertainties within the background estimates, assigned separately to each of the four background sources: uncertainties from the finite size of control samples are constrained with gamma distributions, whereas uncertainties related to statistical fluctuations in multiplicative factors and systematic background uncertainties, are modeled with log-normal distributions.

The expected limits on the cross section are displayed in Figure 6.32 as a function of the chargino mass for various chargino lifetimes. Figure 6.33 shows the expected limits across the complete range of considered masses. The intersection between the theoretical prediction and the expected upper limit on the cross section is utilized to infer a constraint on the chargino mass for each chargino lifetime. This procedure is repeated over the full range of chargino lifetimes to generate a two-dimensional constraint in the plane of chargino mass versus mean proper lifetime, shown in Figure 6.34. Wino-like charginos are expected to be excluded up to masses of 777 (405) GeV for lifetimes of 3 (0.2) ns. Higgsino-like charginos are expected to be excluded up to masses of 650 (354) GeV for lifetimes of 3 (0.2) ns.

By combining the results of this analysis with those obtained from the prior Run 2 studies (2015–2018) [137, 138], the expected cross section limits displayed

in Figure 6.35 are achieved, enhancing the expected exclusion reach to wino-like chargino masses up to 904 (511) GeV for a lifetime of 3 (0.2) ns. In the combined scenario, higgsino-like charginos are expected to be excluded up to masses of 762 (437) GeV for a lifetime of 3 (0.2) ns.

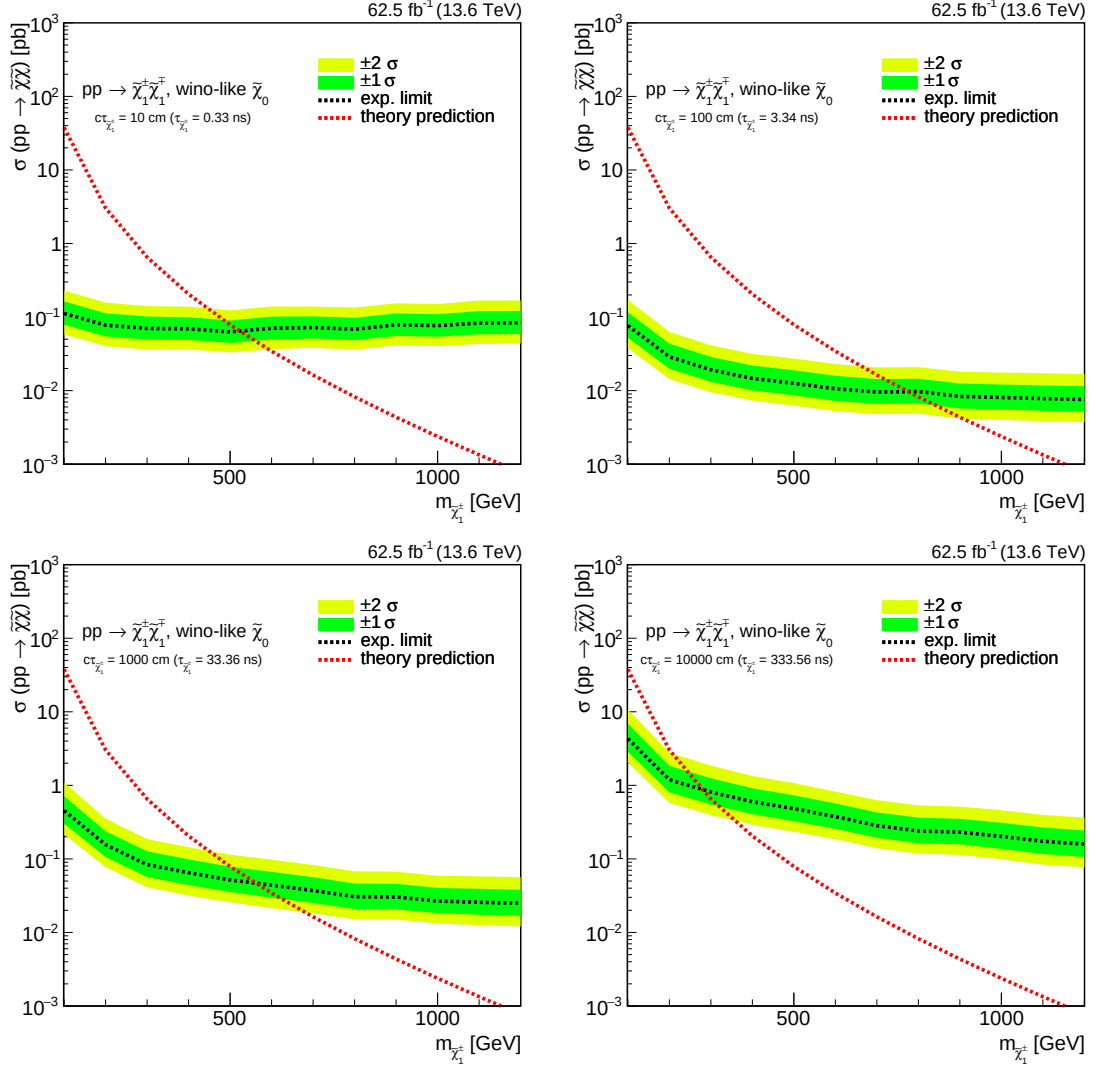


Figure 6.32: Expected 95% CL upper limits on the cross sections for direct chargino production as a function of chargino mass for various chargino lifetimes with a purely wino-like neutralino. These are calculated from the combined 2022 and 2023 results.

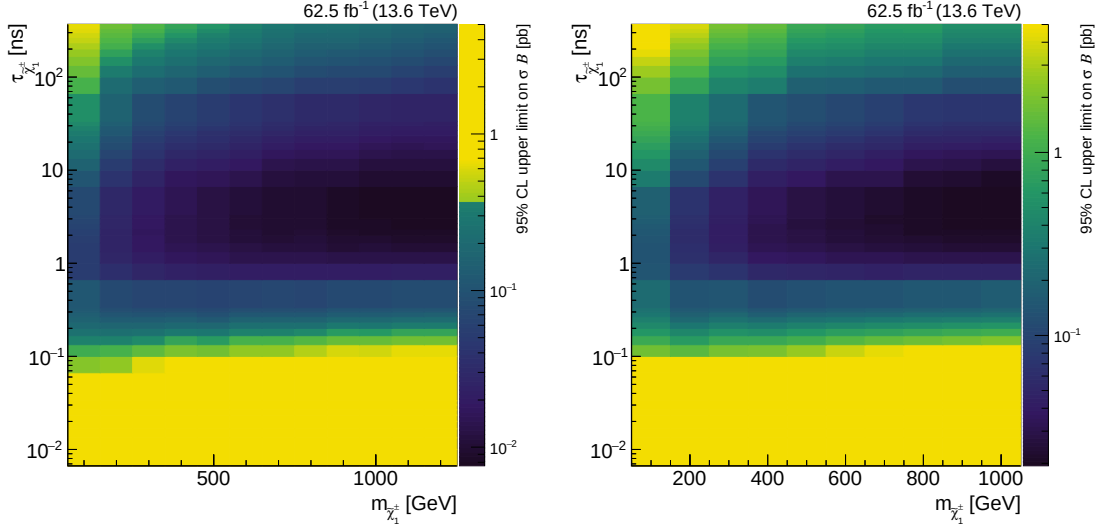


Figure 6.33: Upper limits at 95% CL on the cross section for direct chargino production as a function of chargino mass and lifetime for a purely wino-like neutralino (left) and a purely higgsino-like neutralino (right). The plot shows the expected limits. These are calculated from the combined 2022 and 2023 results.

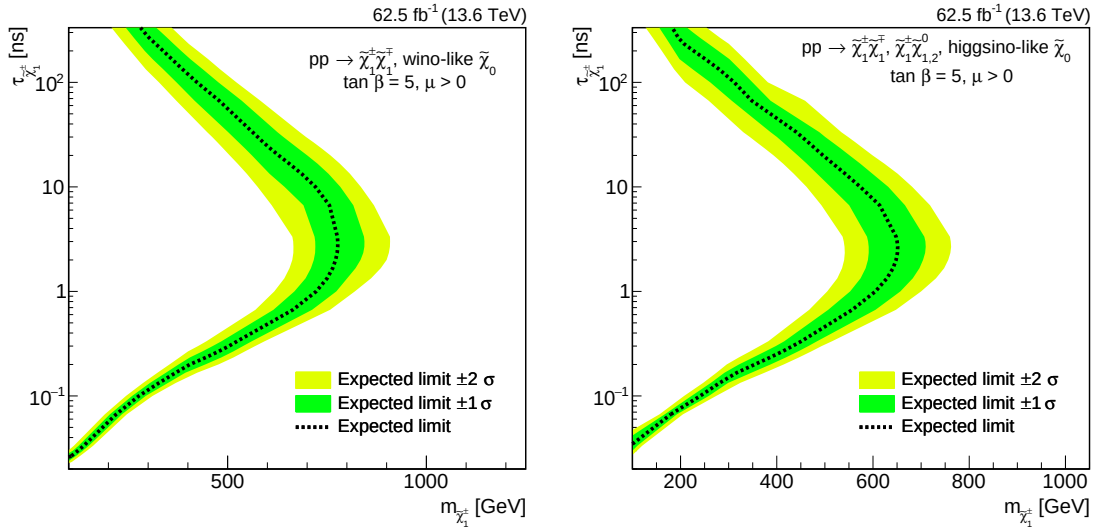


Figure 6.34: Expected constraints on chargino lifetime and mass for a purely wino-like neutralino (left) and a purely higgsino-like neutralino (right). The region to the left of the curve is excluded at 95% CL. These are calculated from the combined 2022 and 2023 results.

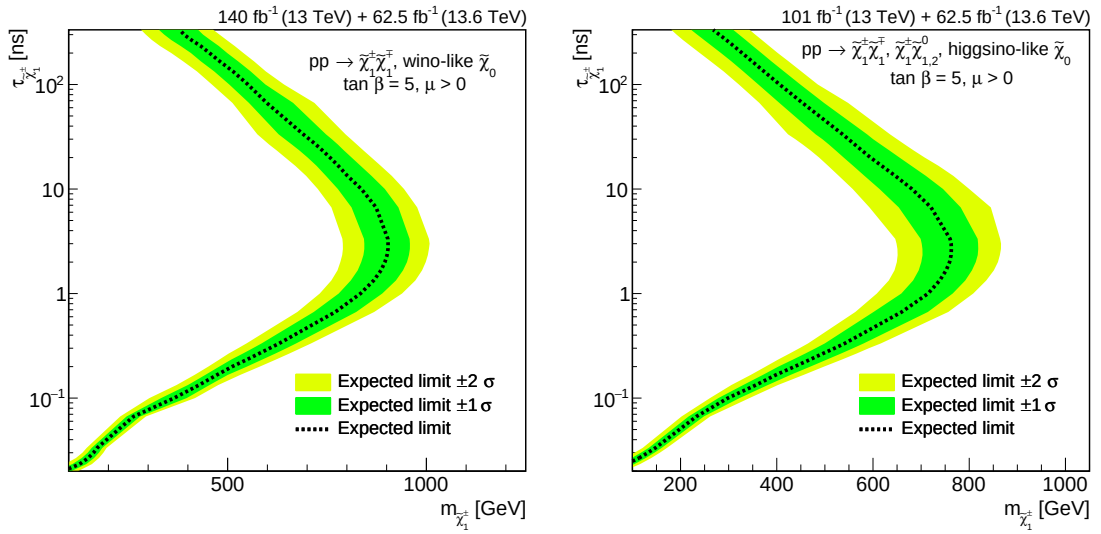


Figure 6.35: Expected constraints on chargino lifetime and mass for a purely wino-like neutralino (left) and a purely higgsino-like neutralino (right), for the results in 2022 and 2023 combined with previously published results in 2015-8 (2017-8 only for the higgsino-like neutralino) for the full Run 2+Run 3 results. The region to the left of the curve is excluded at 95% CL.

Chapter 7

Discussion and Conclusions

Although the Standard Model successfully describes the dynamics of all known elementary particles and accounts for three of the four fundamental forces, certain phenomena remain outside its framework. One long-lasting mystery that has challenged physicists and cosmologists for nearly a century is the existence of missing matter in the universe, commonly called dark matter. Evidence suggests the presence of a new, electrically neutral particle that is stable over cosmological timescales and interacts only weakly with SM particles. If such a particle exists, there is a possibility it could be produced in high-energy particle accelerators, such as the LHC, and detected using experiments like the CMS detector.

A theoretical framework addressing new physics in the context of supersymmetry is the AMSB model. In the cases where the wino- or higgsino-like neutralino is the lightest supersymmetric particle, it becomes a possible DM candidate. Moreover, given its very small mass splitting with the chargino of the model, it can produce the signature of a disappearing track in modern particle detectors. Pairs of charginos or chargino-neutralino can be produced by the LHC and be studied by CMS. The disappearing track signature is of particular interest because there are no SM particles that can mimic this signal.

One issue with the disappearing track signature is related to the triggering of events. At the L1T, the only way to select events of interest is if the produced pair of electroweakinos recoils against an ISR parton. Also, at the HLT, even though dedicated paths are deployed to capture the p_T^{miss} + isolated track signature, the rate at which the events are collected is on the order of 5 Hz.

This work had two main objectives. The first was to solve two issues faced by the reconstruction of HLT events, which were: harder maintainability, due to code duplication, and an unwanted exclusive coupling between the software and the currently deployed hardware accelerator devices. The second objective was

to perform the analysis of 62.5 fb^{-1} data collected by the CMS detector during the early Run 3 (2022 and 2023) with a center-of-mass energy of $\sqrt{s} = 13.6 \text{ TeV}$, to search for a disappearing track signal. While performing the search, two main changes to the analysis framework were studied and implemented: the production of signal events using the MadGraph5 + Pythia8 combination, and the usage of the MiniAOD data format with the change in the way the E_{calo} variable is used.

The modification of the HLT pixel tracks reconstruction to use the Alpaka library benefits the whole CMS collaboration. As already mentioned, an improvement in efficiency or timing is not observed or expected. The main impact of this modification is opening up the possibility of more diverse processing/accelerator devices and on the flexibility of the development of new algorithms for data processing, while allowing for easy maintainability. These changes will improve the capability of the collaboration to collect and analyze data in the future.

Given that the disappearing tracks search is still blinded by the CMS collaboration, a statistical analysis of the estimated number of background events in the signal region was performed. The results were interpreted in terms of exclusion regions with 95% CLs. Considering the Run 3 data only, a wino-like chargino is expected to be excluded up to a mass of 777 (405) GeV for a lifetime of 3 (0.2) ns, while a higgsino-like chargino is expected to be excluded up to a mass of 650 (354) GeV for a lifetime of 3 (0.2) ns. When combining this result to the previous Run 2 results, a wino-like chargino is expected to be excluded up to a mass of 904 (511) GeV for a lifetime of 3 (0.2) ns, while a higgsino-like chargino is expected to be excluded up to a mass of 762 (437) GeV for a lifetime of 3 (0.2) ns.

Even though this search was not completed, it served as a stepping stone for the next version of the analysis. Some examples of improvements that will be performed in the future version of this analysis are: usage of $p_{\text{T}}^{\text{miss}}$ and jets with the PUPPI pileup removal algorithm; usage of machine learning algorithms for identification of charged leptons, which will improve the veto of background events, and fake tracks, to better classify tracks as true disappearing tracks or not; and the combination of the results with more data, such as the 122.2 fb^{-1} of pp collision data collected during 2024.

Appendix A

Generation of LHC Hadronic Jets using Generative Networks

PAPER • OPEN ACCESS

LHC hadronic jet generation using convolutional variational autoencoders with normalizing flows

To cite this article: Breno Orzari *et al* 2023 *Mach. Learn.: Sci. Technol.* **4** 045023

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OPEN ACCESS

RECEIVED
27 June 2023REVISED
9 October 2023ACCEPTED FOR PUBLICATION
19 October 2023PUBLISHED
31 October 2023

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LHC hadronic jet generation using convolutional variational autoencoders with normalizing flows

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Keywords: generative models, particle physics, high energy physics, hyperparameter tuning

Abstract

In high energy physics, one of the most important processes for collider data analysis is the comparison of collected and simulated data. Nowadays the state-of-the-art for data generation is in the form of Monte Carlo (MC) generators. However, because of the upcoming high-luminosity upgrade of the Large Hadron Collider (LHC), there will not be enough computational power or time to match the amount of needed simulated data using MC methods. An alternative approach under study is the usage of machine learning generative methods to fulfill that task. Since the most common final-state objects of high-energy proton collisions are hadronic jets, which are collections of particles collimated in a given region of space, this work aims to develop a convolutional variational autoencoder (ConVAE) for the generation of particle-based LHC hadronic jets. Given the ConVAE's limitations, a normalizing flow (NF) network is coupled to it in a two-step training process, which shows improvements on the results for the generated jets. The ConVAE+NF network is capable of generating a jet in $18.30 \pm 0.04 \mu\text{s}$, making it one of the fastest methods for this task up to now.

1. Introduction

In the CERN Large Hadron Collider (LHC) [1, 2], approximately one billion proton–proton (pp) collisions occur every second. Those collisions generate outgoing particles that are measured by dedicated, custom-made particle detectors. The main data stream collected by such a detector is close to 1.4 kHz. After the upcoming LHC upgrade to the high-luminosity LHC (HL-LHC) [3] this number will increase by a factor of 3.5–5. In high energy physics (HEP), an important part of the data analysis is the simulation of pp collisions that are used to test analysis techniques, estimate the particle detectors' efficiencies and resolutions, and make comparisons with collected data. Usually, the number of simulated events is an order of magnitude higher than the number of recorded events in real data, such that the statistical uncertainty of the simulated events does not dominate the overall uncertainty. For simulating collision data, Monte Carlo (MC) event generators are used. However, the increased granularity of the detectors and the higher complexity of the collision events after the HL-LHC upgrade pose significant challenges that cannot be solved by increasing the computing resources alone [4].

One of the most common final-state objects in high-energy pp collisions is an energetic cluster of hadrons, known as a hadronic jet [5]. Jets can be described by the features of their constituent particles, mainly their four-momentum. The particle-flow [6] algorithm is used to combine information obtained by several sub-detectors to precisely measure each particle's properties. Jet clustering algorithms [7] can be used

to cluster the particle constituents into a jet and obtain its relevant properties for physics analysis such as its invariant mass, transverse momentum (p_T), energy, azimuthal angle ϕ , and pseudorapidity η ⁵.

Being able to accelerate the process of jet simulation in a particle detector would be of great advantage to mitigate the needed overhead in computing resources. One of the avenues that shows promising results is the use of generative machine learning (ML) algorithms to perform the jet simulation. The goal of this program is to maintain the accuracy of MC methods while making the process orders of magnitude faster. Several approaches using neural networks (NNs) have been studied and applied for this purpose, using generative adversarial networks (GANs) [8, 9], normalising flows [10], and score-based diffusion models [11, 12]. Another promising technique is the use of variational autoencoders (VAEs) [13], which have yet to demonstrate high fidelity results.

In this work, a new method for the generation of hadronic jets from noise is presented. It is based on a VAE coupled with a normalizing flow (NF) and trained in a two-step process. This technique opens up a path to explore and further our expertise in generating point-cloud-like-objects in general, and in this paper we focus on a possible application in HEP. The paper is organized as follows. Section 2 contains a literature overview of ML applied to HEP, mainly focusing on generative methods for jets simulation. In section 3 the dataset and the model are described. Section 4 details the custom loss function and the evaluation metrics; results are presented and discussed in section 5. Finally in section 6, we summarize the work and give an outlook for using the new method.

2. Related work

ML techniques have been applied to hadronic jets generation following several distinct approaches. Some of the first attempts [14, 15] were performed using convolutional neural networks (CNNs) because of their impressive results in computer vision and the fact that an image-like representation of a jet arises naturally from the particle detectors' data. For a similar reason, the use of CNNs for the simulation of calorimeter showers [16–18] were explored. Other jet representations such as vectors of energy deposits in calorimeters or high-level jet characteristics have also been studied [19, 20].

Recently, particle-based jet datasets have also been extensively used by the ML community in the context of jets generation [8, 9, 13, 21]. They are composed of the jets constituent particles' properties and give a detailed description of particles distribution inside the jet, which is known as the jet substructure [22, 23]. GANs based on graph networks [8, 9] have provided inspiring results when aiming to generate particle-based jets, retaining great similarity between generated jets and MC simulated jets while improving the speed of simulation by 4 to 5 orders of magnitude depending on the number of particles inside the generated jet. Some VAEs based on convolutional networks have also been implemented using the same dataset for jets fast simulation [21] and for the jets generation as well [13]. However, for the latter, there is great room for improvement when comparing the VAE generated jets with MC simulated jets.

The premise of this work is that the VAE by itself is not enough to capture the full characteristics of a hadronic jet, mainly due to the *a priori* choice of the latent space distribution. On the other hand, a combined VAE+NF approach, which has already been applied for image generation [24], time series data prediction [25] and calorimeter shower simulation [26, 27], among others, has not yet been applied in the context of hadronic jets generation. In this work, this combined approach is used to improve the generative capacity of the VAE.

3. Dataset and model

We use the gluon HLS4ML LHC Jet dataset [28, 29] that is composed of ~ 177 k gluon jets, containing the jet constituent particles' three-momenta (p_x, p_y, p_z). These were obtained from simulated pp collisions with a center of mass energy of $\sqrt{s} = 13$ TeV that produced jets with $p_T \approx 1$ TeV. A simplified particle detector parameterization, similar to the apparatuses deployed by the large LHC experiments, is used to emulate the detector response. The hadronic jets are reconstructed using the anti- k_T algorithm [30, 31] with a distance parameter $R = 0.8$. The 177 k samples are divided into $\sim 70\%$ for training and $\sim 15\%$ each for validation and testing. Even though there is no intrinsic ordering to the particles inside a jet, the particles are ordered in a list by decreasing p_T and only the first 30 particles are used as input to the ML algorithm. If a jet contains less than 30 particles, the rest of the list was filled with zeros (zero-padding). A feature-wise standardization was performed to bound the values of the three-momentum to be in the range $[0.0, 1.0]$ as input to the network.

⁵ In the LHC experiments, the origin of the right-handed coordinate system is the center of the local pp collision region, the y axis is defined vertically upward, and the z axis is along the proton beam direction. Additional coordinates are the azimuthal angle ϕ and pseudorapidity $\eta = -\ln \tan(\theta/2)$, where θ is the polar angle.

Table 1. Sequential layers of a representation of the encoder of the ConVAE model. The sizes of the Conv2D and Linear layers are given as [input channels, output channels, kernel size[0], kernel size[1]] and [input nodes, output nodes], respectively. The decoder architecture is an exact mirror of the encoder up to the last linear layer, using 2D deconvolution layers. An activation function is applied after all layers, except for the last linear layer of the encoder. The activation function, number of filters, kernel size, linear size and latent dimension size were obtained via hyperparameter optimization.

Layer type	Size	ℓ
Input list	[1, 3, 30]	—
Conv2D	[1, N_{filters} , 3, kernel size]	1
Conv2D	[$2^{\ell-2} \times N_{\text{filters}}$, $2^{\ell-1} \times N_{\text{filters}}$, 1, kernel size]	2
Conv2D	[$2^{\ell-2} \times N_{\text{filters}}$, $2^{\ell-1} \times N_{\text{filters}}$, 1, kernel size]	3
Linear	[$2^{\ell-2} \times N_{\text{filters}} \times (30 - (\text{kernel size} - 1) \times (\ell - 1))$, linear size]	4
Linear	[linear size, $2 \times \text{latent dimension size}$]	—
Mean & Variance	latent dimension size	—
Latent vector	latent dimension size	—

3.1. Convolutional VAE

To accommodate this representation of the input dataset, the chosen model is a VAE [32–34] composed of convolution layers (ConVAE). The VAE is composed of three components: (i) an encoder, which learns to compress the representation of the input data into a lower dimensional representation, (ii) a latent space, which stores this lower dimensional representation into values that closely follow a probability distribution defined by the user, and (iii) a decoder, which decodes the latent space values to the output. The probability distribution of the latent space values has to be differentiable, easy to implement, and easy to sample from. The most common choice is the standard Gaussian $\mathcal{N}(0, 1)$. The goal of the VAE is to produce output data whose distribution is as similar as possible to that of the input data. In addition, it is desirable to be able to generate new data samples resembling the training data by sampling from $\mathcal{N}(0, 1)$ and feeding those values into the decoder.

The network was implemented in the PyTorch library [35]. In this work, the encoder and decoder structures are mirrored, and only the encoder will be described. It is composed of a given number of consecutive two-dimensional convolution layers where the last convolution layer is flattened and introduced into two linear layers, where the latter is input into the latent space. An activation function is applied after each layer, except for the last linear layer of the encoder. The input and output layers of the network have a fixed size of 3×30 . The activation function in between each layer, number of convolutional layers in the encoder and decoder, kernel size, latent dimension size, number of filters, and number of nodes in the linear layers between encoder (decoder) and the latent space are hyperparameters to be optimized. The activation function of the last deconvolution layer of the decoder was chosen to be the sigmoid [36] function, to bound the output values in between 0.0 and 1.0, given the feature-wise standardization.

In the encoder architecture, the number of input nodes of the first linear layer is fixed by the size of the last convolutional layer, while the number of output nodes of the second linear layer is fixed as two times the number of dimensions of the latent space to provide the means and standard deviations of the latent distributions⁶. In the decoder architecture, the number of input nodes in the first linear layer is fixed by the latent space size, and the number of output nodes in the second linear layer is fixed by the size of the first deconvolution layer. The stride and padding of the convolution layers were kept as 1 and 0, respectively. The first convolutional layer has 1 input filter and N_{filters} output filters, and the rest of the convolutional layers have an input number of filters equal to $2^{\ell-2} \times N_{\text{filters}}$ and an output number of filters equal to $2^{\ell-1} N_{\text{filters}}$, where ℓ is the layer number. Using as an example an encoder of a ConVAE composed of three convolutional and two linear layers, table 1 summarizes the sequential layers of the network.

At training time, the batch size was kept fixed at 100 samples and the Adam optimizer [37] was used with a learning rate (LR) that was set by the hyperparameter optimization.

3.2. Normalizing flows

When the ConVAE is optimized for reconstruction, i.e. the importance of the reconstruction loss term (detailed in section 4) is small, a looser constraint is applied to ensure the latent space values follow a given probability distribution. In this case, the probability distribution of the latent space values, $p(\mathbf{z})$, favors optimizing the reconstruction rather than strictly matching an imposed prior. These reconstruction-imposed latent space distributions are generally unknown and one cannot easily sample from them.

A NF [38, 39] is a transformation of a simple probability distribution (e.g. $\mathcal{N}(0, 1)$) into a more complex distribution (and vice versa) through a sequence of invertible and differentiable mappings usually learned by

⁶ A.k.a., the reparametrization trick [34].

training a NN. Therefore, we can combine the ConVAE approach with a NF to find the transformation from the more complex latent space distribution to a simpler one, such as $p(\mathbf{z}) \xrightarrow{f} u(\mathbf{x})$ where $u(\mathbf{x}) = \mathcal{N}(0, 1)$. Since these transformations are invertible by construction, it is possible to start from values that follow the simple distribution, pass it through the inverse of the transformation and obtain values that follow the complex and unknown distribution as $u(\mathbf{x}) \xrightarrow{f^{-1}} p(\mathbf{z})$. The network is trained by maximizing the right-hand side of equation (1).

$$\ln(p(\mathbf{z})) = \ln(u(f(\mathbf{z}))) + \ln \left| \det \left(\frac{\partial f(\mathbf{z})}{\partial \mathbf{z}} \right) \right|, \quad (1)$$

where $\partial f(\mathbf{z})/\partial \mathbf{z}$ is the Jacobian of the transformation.

The NF network we use is based on the RealNVP network⁷ [40, 41] that makes use of simple analytic expressions for each intermediate transformation

$$y_{1:d} = x_{1:d}, \quad (2)$$

$$y_{d+1:D} = x_{d+1:D} \cdot \exp(s(x_{1:d})) + t(x_{1:d}), \quad (3)$$

using the coupling layers [42], where only a subset of the input data undergoes the transformations while the rest remains unchanged, and the subsets are permuted every epoch to ensure that all input data goes through the flows. The parameters s and t are obtained as the outputs of two multilayer perceptrons (MLPs), which can be as complex as needed.

The NF network was implemented using the PyTorch library. The Adam optimizer was chosen to update the network parameters by minimizing the negative of the mean of the expression in equation (1) as the loss function. The LR, number of flows and the number of layers and nodes of the two MLPs that determine s and t were hyperparameters to be optimized. The ReLU [43] activation function was used for each layer of the MLPs, and for s the hyperbolic tangent was used after its last layer to constrain its values to be in the range $(-1.0, 1.0)$. The number of input and output nodes of the s and t networks were set to match the number of latent dimensions of the ConVAE.

4. ConVAE loss function and evaluation metric

To define a customized loss function for the ConVAE model, we adapt the standard VAE loss [32], which is given by the expression:

$$L(\theta, \phi) = -\mathbb{E}_{\mathbf{z} \sim q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\theta(\mathbf{x}|\mathbf{z})] + D_{\text{KL}}(q_\phi(\mathbf{z}|\mathbf{x}) \parallel p(\mathbf{z})), \quad (4)$$

where $\mathbf{x}$ is the vector of data values, $\mathbf{z}$ is the vector of latent space values, $q_\phi(\mathbf{z}|\mathbf{x})$ the variational posterior (i.e. the encoder), $p_\theta(\mathbf{x}|\mathbf{z})$ the conditional likelihood (i.e. the decoder), and $p(\mathbf{z})$ the prior distribution. The first term on the right-hand side can be seen as the reconstruction loss L_{rec} , measuring the distance between the output produced by the network and the input data. The second term D_{KL} is the Kullback–Leibler divergence [44] that measures the difference between the probability distributions of the encoder output values and the latent space values. The distribution of the latent space values is defined *a priori*, and the distribution of the encoder output values is one that is easy to work with, but still complex enough to describe its output, where the usual choice is a multivariate Gaussian.

The minimization of this loss function ensures that the output will be as close as possible to the input, while the values of the latent space closely follow the chosen distribution. In addition, one can add a hyperparameter β [45] to control the importance of each term in the loss. The loss function can be written as:

$$L_{\text{VAE}} = (1 - \beta)L_{\text{rec}} + \beta D_{\text{KL}}. \quad (5)$$

The reconstruction loss term was customized to the task of particle generation. The loss function that compares output particles with input dataset particles was chosen to be the Chamfer distance [46], also referred to as nearest neighbor distance (NND). This loss function is preferred over the commonly-used

⁷ The implementation of the RealNVP network in this work was performed following the GitHub repository <https://github.com/ispamm/realnvp-demo-pytorch>.

mean-squared error (MSE) function because it is permutation invariant, which is desirable since particles in a jet have no intrinsic ordering. The NND loss is expressed as:

$$L^{\text{NND}} = \sum_k \left[\sum_{i \in \mathcal{J}_k} \min_{j \in \hat{\mathcal{J}}_k} D(\vec{p}_i, \vec{\hat{p}}_j) + \sum_{j \in \hat{\mathcal{J}}_k} \min_{i \in \mathcal{J}_k} D(\vec{\hat{p}}_j, \vec{p}_i) \right], \quad (6)$$

where i and j are indices of the particles in the input and output samples, respectively, k is the index of a given jet, $\mathcal{J}_k$ represents the k -th jet in the dataset, $\hat{\cdot}$ distinguishes between input (without) and output (with) objects, and $D(\vec{p}_i, \vec{\hat{p}}_j)$ is the Euclidean distance between input and output particles, treating each as a vector in (p_x, p_y, p_z) space. The first term finds the closest output particle to a given input particle, the second term finds the closest input particle to a given output particle, and their distances are summed.

The loss L^{NND} alone was not enough to provide good quality of the generated jets. Therefore, physics-inspired constraints were included in the form of distances between the input and output jet properties. The best results were achieved using a combination of the jet mass and p_T terms using MSE as a distance function. The additional loss term was added as follows

$$L^J = \sum_k [\gamma_{p_T} \text{MSE}(p_{T_k}, \hat{p}_{T_k}) + \gamma_m \text{MSE}(m_k, \hat{m}_k)]. \quad (7)$$

where the parameters γ_{p_T} and γ_m were used to weight each contribution. Finally, the combined reconstruction loss is given by

$$L_{\text{rec}} = \mathbb{E}_{\hat{\mathcal{J}} \sim r_{\phi, \theta}(\mathcal{J} | \mathcal{J})} [\alpha L^{\text{NND}} + \gamma L^J], \quad (8)$$

in which α and γ were used to weight the importance of each contribution to the loss function and $r_{\phi, \theta}(\hat{\mathcal{J}} | \mathcal{J})$ represents the full VAE probability distribution from input to output. The full set of loss parameters $(\alpha, \beta, \gamma, \gamma_{p_T}, \gamma_m)$ was optimized via hyperparameter optimization.

The evaluation metric chosen to quantitatively measure the generation capabilities of the distinct models was the earth mover's distance (EMD) [47], or 1-Wasserstein distance, calculated for each histogram of the input and output jets mass, energy, p_T , η , and ϕ , and summed to get the EMD_{sum} . The choice of the variables was based on relevant quantities for jet-based searches in LHC experiments [48, 49]. This metric was used as the hyperparameter optimization objective, the method to choose the best model, and to compare different approaches.

The hyperparameter optimization was performed using the Optuna package [50], which allows for fast convergence thanks to aggressive pruning based on intermediate results and easy parallelization. Each ConVAE was set to go through 300 trials of the optimization, where each trial was executed for 300 epochs of the training. The procedure was carried out in two steps. In the first, only the loss parameters and the optimizer LR were optimized while the network parameters were fixed at some reasonable choices established after manual tests. In the second, all the network parameters were optimized given the best set of loss parameters. This was done to ensure convergence of the optimization procedure in a feasible amount of time given the amount of resources available. During the optimization, the EMD_{sum} was minimized using the value evaluated on the validation dataset after every 5 epochs.

To combine the ConVAE with the NF network (ConVAE+NF), a two-step training was performed. First, the hyperparameters of the ConVAE were optimized and the resulting best model was trained for 1500 epochs. The model with the smallest EMD_{sum} when comparing the input with reconstructed jets in the validation dataset, calculated every 5 epochs, was saved. The latent space values of the saved network when receiving as input the training and validation jet datasets were extracted to generate new training and validation datasets for the NF. A diagram containing the full training procedure is displayed in figure 1.

The metric used to evaluate the combination of both networks as the hyperparameter optimization objective was EMD_{sum} . After every four epochs, N_{latent} values were sampled from $\mathcal{N}(0, 1)$ and input into the inverse of the NF network, whose output was given as input to the decoder of the ConVAE tuned for reconstruction, and its output was compared with jets from the validation dataset. The optimization was run for 300 trials with 20 epochs of NF training per trial. The best set of hyperparameters was used to train the final NF network for 100 epochs, and the model that exhibited the smallest metric value, checked after every epoch, was saved.

5. Results and discussion

5.1. Hyperparameter optimization

As described above, the hyperparameter optimization was performed using the Optuna framework and executed in steps to speed up the convergence of the method given the limited computational resources. The

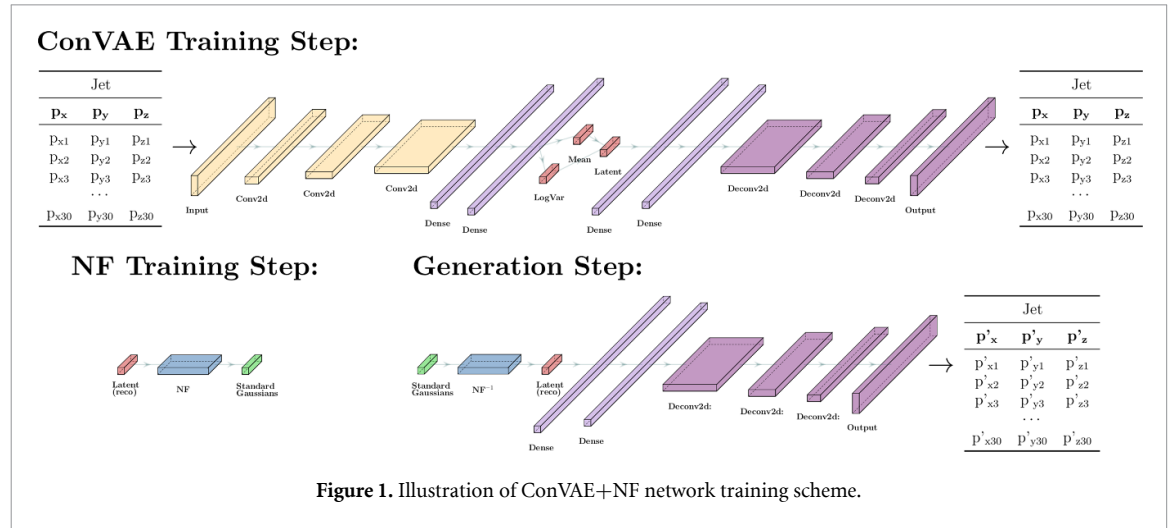


Table 2. Set of common architecture hyperparameters for ConVAE loss parameters optimization.

N_{latent}	Filters	Kernel	N_{linear}	Layers	Act. Func.
30	50	5	1500	3	ReLU

Table 3. Ranges of common architecture hyperparameters for ConVAE loss parameters optimization. The choice of activation function was also optimized, chosen from one of ReLU, GeLU, LeakyReLU, SELU or ELU.

LR	α	γ	γ_{p_T}	γ_m
10^{-5} – 10^{-1}	0.1–1.0	0.1–1.0	0.8–1.2	9.986–14.98
N_{latent}	Filters	Kernel	N_{linear}	Layers
10–300	5–100	1–8	100–3000	1–4

ranges considered for each hyperparameter during the optimization for both types of NN are shown below. In the ConVAE case, the set of parameters to be optimized was: the LR of the optimizer (Adam), the loss function parameters α , β , γ , γ_{p_T} , and γ_m , and the architecture parameters as the number of latent dimensions, number of filters, kernel size related to the number of particles to convolve, number of nodes in linear layers, number of convolution layers, and activation function. For the 2D kernel size (k_1, k_2) , only k_2 , the number of particles to convolve, was varied, while k_1 , the number of particle features to convolve, was set to 3 for the first (last) convolution (deconvolution) layer of the encoder (decoder) and 1 otherwise.

The ranges of the parameters γ_{p_T} and γ_m were determined by the dataset because jet p_T and mass have different scales, which imply different magnitudes for those loss components. The range for γ_{p_T} was set from 20% smaller to 20% larger than unity, while the range for γ_m was set from 20% smaller to 20% larger than the ratio of the mean of the jet p_T and mass. For the loss function hyperparameter optimization, the network architecture hyperparameters were fixed at the reasonable choices displayed in table 2. For both ConVAE networks (ConVAE and ConVAE+NF approaches) almost all the ranges of the hyperparameters for the optimization were the same, and are shown in table 3. The only exception was for the loss hyperparameter β that, due to the difference in the magnitudes of L_{rec} and D_{KL} , needed to be much closer to 1.0 for the ConVAE tuned for generation, where the optimization range was [0.9, 1.0] in log scale, and much closer to 0.0 for the ConVAE tuned for reconstruction, where the optimization range was [0.0, 0.1] in log scale.

Since the number of hyperparameters of the RealNVP network is much smaller than for the ConVAE, its hyperparameter optimization was performed only in one step. The set of hyperparameters that were optimized was: the LR of the optimizer (Adam); and the network architecture hyperparameters as the number of flows, number of linear layers for the s and t MLPs and the number of nodes in each layer of those MLPs. For both the RealNVP network used together with the ConVAE and the one used by itself, the ranges of the hyperparameter optimization are shown in table 4.

5.2. Experiments

We experiment with three approaches: a baseline ConVAE-only model, the ConVAE+NF model, and another baseline NF-only model. The final set of optimized hyperparameters for the former is displayed in

Table 4. Ranges of architecture hyperparameters for the RealNVP optimization. The number of nodes in each linear layer (N_{linear}) is optimized separately for each layer.

LR	N_{flows}	Layers	N_{linear}
10^{-5} – 10^{-1}	5–100	1–4	50–400

Table 5. Set of optimal hyperparameters for the ConVAE tuned for generation.

LR	α	β	γ	γ_{p_T}	γ_m	N_{latent}	Filters	Kernel	N_{linear}	Layers	Act. Func.
6.1×10^{-4}	0.449	0.998	0.118	0.817	11.7	190	75	3	1100	4	ReLU

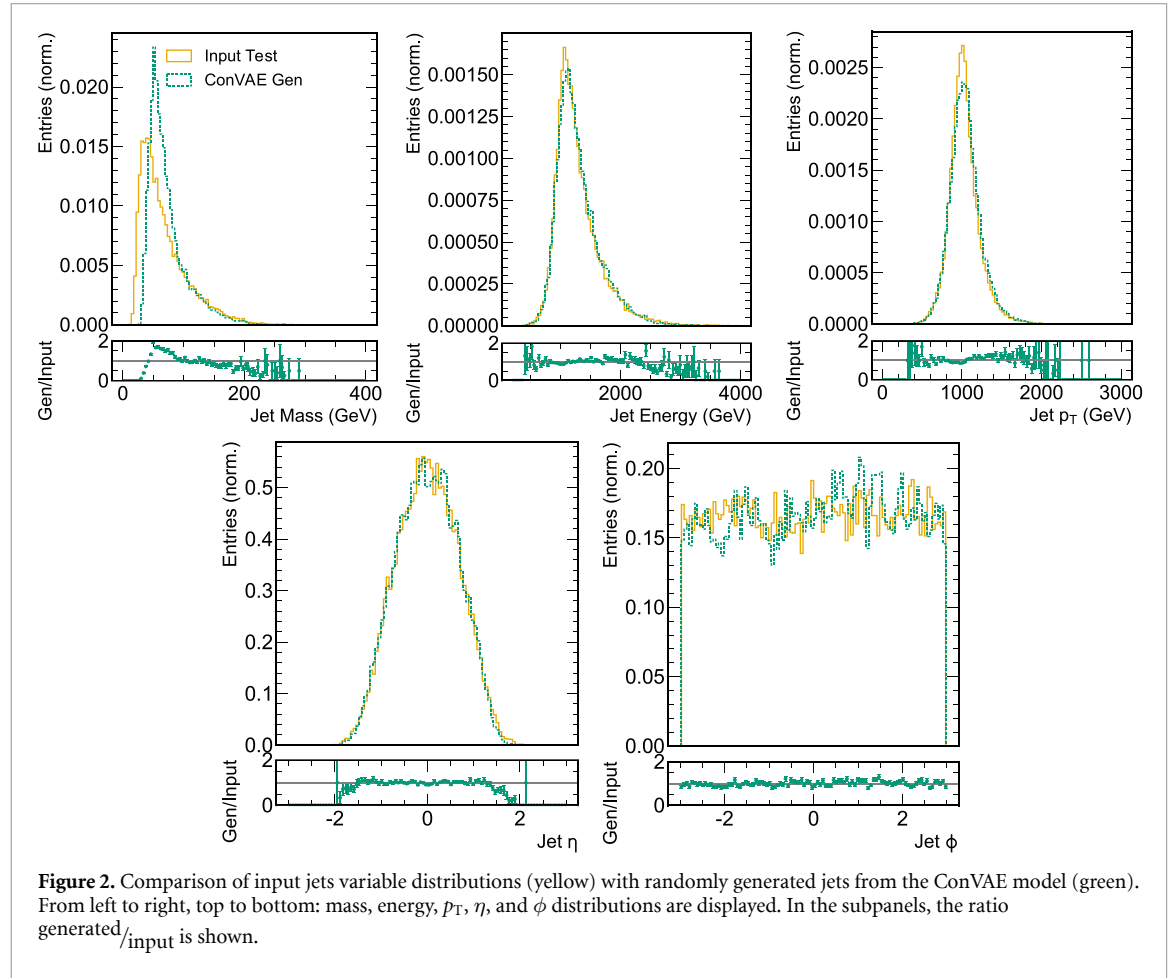


Figure 2. Comparison of input jets variable distributions (yellow) with randomly generated jets from the ConVAE model (green). From left to right, top to bottom: mass, energy, p_T , η , and ϕ distributions are displayed. In the subpanels, the ratio generated/input is shown.

table 5, which result in an EMD_{sum} value of 0.0033. Figure 2 shows the comparisons of the distributions of input and output jet mass, p_T , energy, η and ϕ after hyperparameter optimization. Qualitatively, the distributions of jet energy, η , and ϕ are very similar, with differences only at the extremes of the histograms, while for p_T there is a slight difference at the peak of the distribution and small discrepancies at both tails. The greatest discrepancies are in the distributions of jet mass, where they are only similar in the approximate range $80 \text{ GeV} < m_{\text{jet}} < 175 \text{ GeV}$.

The complete sets of optimized hyperparameters for the ConVAE+NF model are displayed in tables 6 and 7, which result in an EMD_{sum} of 0.0026. The histograms of the jet variables are displayed in figure 3.

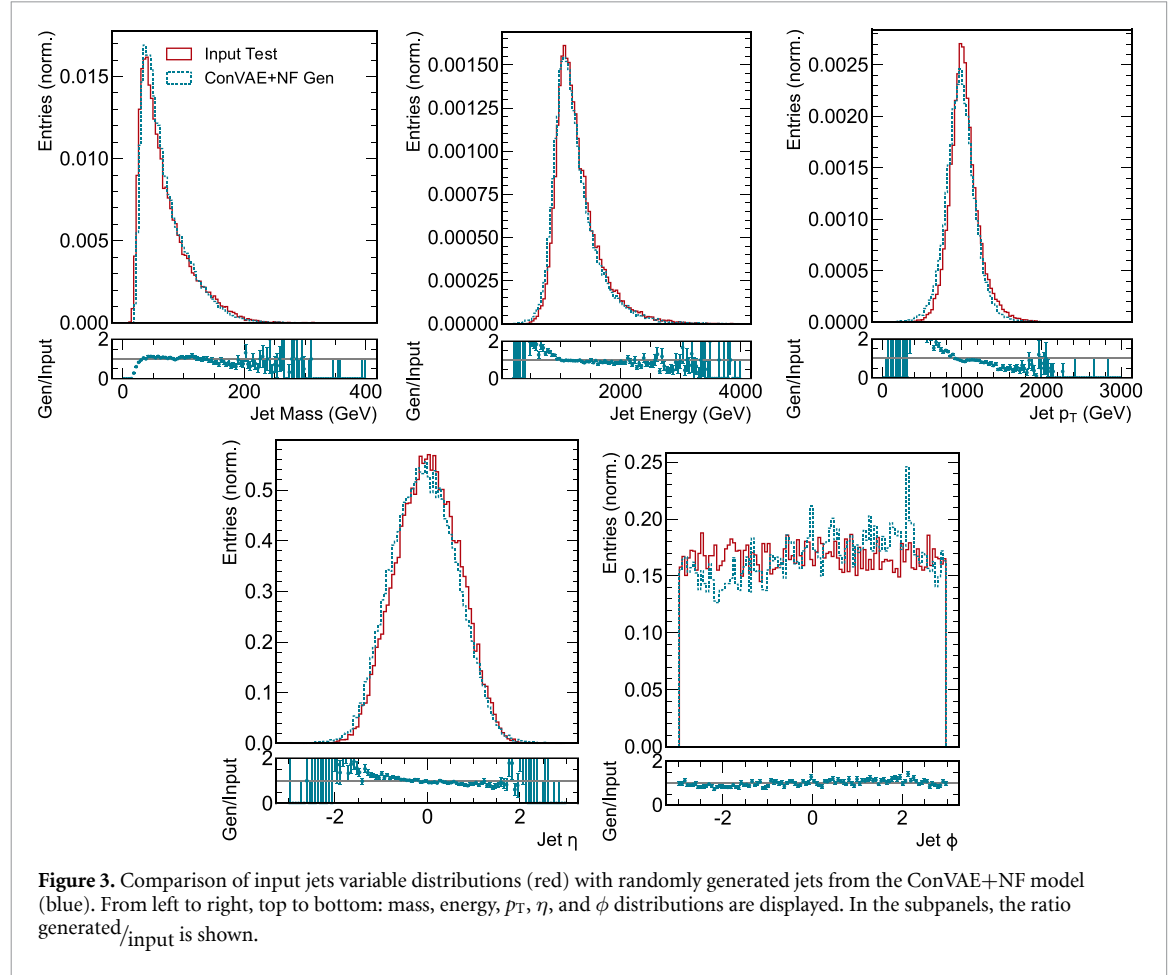
Based on the EMD_{sum} , there is a large improvement in the generative capabilities of the ConVAE+NF model compared to the ConVAE model. In particular, the agreement in the jet mass distribution improves dramatically, with disagreement only for masses smaller than 25 GeV. However, there remain notable deviations from unity in the η , ϕ , and p_T histograms ratio between randomly generated and input jets.

Table 6. Set of optimal hyperparameters for ConVAE tuned for reconstruction.

LR	α	β	γ	γ_{p_T}	γ_m	N_{latent}	Filters	Kernel	N_{linear}	Layers	Act. Func.
5.3×10^{-4}	0.425	0.046	0.121	1.15	11.8	180	50	2	3000	4	ReLU

Table 7. Set of optimal hyperparameters for the NF to be used on the ConVAE+NF approach.

LR	N_{flows}	Layers	N_{linear}
2.9×10^{-4}	55	4	[400, 350, 400, 400]

**Figure 3.** Comparison of input jets variable distributions (red) with randomly generated jets from the ConVAE+NF model (blue). From left to right, top to bottom: mass, energy, p_T , η , and ϕ distributions are displayed. In the subpanels, the ratio generated/input is shown.**Table 8.** Set of optimal hyperparameters for the NF.

LR	N_{flows}	Layers	N_{linear}
3.4×10^{-4}	65	4	[150, 200, 350, 150]

For comparison, a RealNVP network was also optimized, in the same way as the NF network for the ConVAE+NF approach, and trained to receive as input a flattened jet⁸, transform each feature distribution into an uniform normal, and invert the transformation back to flattened jets. Table 8 contains the set of best parameters after hyperparameter optimization for this network. The value of EMD_{sum} for this case was 0.0049 and the histograms of jet variables are shown in figure 4. The agreement between the distributions and the EMD_{sum} are significantly worse than ConVAE+NF, demonstrating the advantage in combining the inference capability of the ConVAE, with the invertibility of the NF network.

Following the work in [8, 51], another set of metrics was calculated and compared to the results obtained using the state-of-the-art message-passing generative adversarial network (MPGAN) on this dataset. The

⁸ The input jet 3×30 feature matrix representing each particle's p_x , p_y and p_z , was flattened to a 1×90 feature vector containing all particles' p_x , then all p_y and, finally, all p_z .

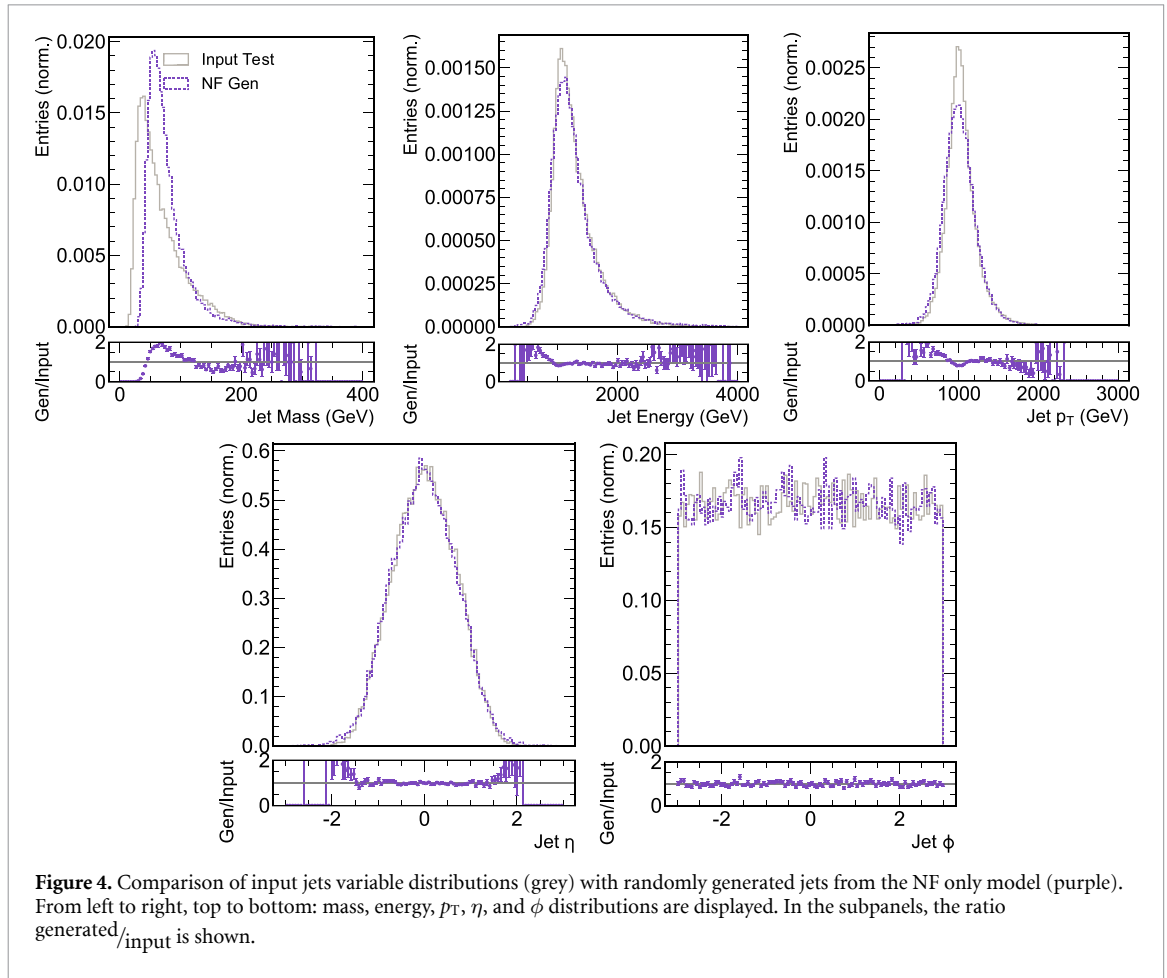


Figure 4. Comparison of input jets variable distributions (grey) with randomly generated jets from the NF only model (purple). From left to right, top to bottom: mass, energy, p_T , η , and ϕ distributions are displayed. In the subpanels, the ratio generated/input is shown.

Table 9. Set of metrics proposed in [8, 51] to compare the performance of distinct ConVAE and NF approaches. In bold are the best values of the metrics when comparing the methods implemented in this work. The last rows display the performance of the MPGAN and EPiC-GAN for the same gluon jet dataset.

Model	$W_1^M (\times 10^{-3})$	$W_1^P (\times 10^{-3})$	$W_1^{\text{EFP}} (\times 10^{-5})$	FPND	COV $\uparrow$	MMD
ConVAE	9.1 ± 0.6	8.5 ± 0.8	576 ± 1035	43.6	0.32	0.036
ConVAE+NF	4.5 ± 0.5	5.3 ± 0.4	197 ± 247	34.3	0.38	0.034
NF	12.7 ± 0.7	8.5 ± 0.8	$8.6\text{k} \pm 13.2\text{k}$	93.6	0.38	0.033
MPGAN	0.7 ± 0.2	0.9 ± 0.3	0.7 ± 0.2	0.12	0.56	0.037
EPiC-GAN	0.3 ± 0.1	1.6 ± 0.2	0.4 ± 0.2	1.01	—	—

metrics W_1^M , W_1^P and W_1^{EFP} correspond to the average 1-Wasserstein distance between input and generated jets mass, constituents η^{rel} , ϕ^{rel} and p_T^{rel} , and five energy-flow polynomials (EFPs) [52], which are a set of variables that capture n -point particle correlations and jet substructure. The computation of the EFPs was performed using the JETNET package [53], where the EFPs correspond to the default choice defined in the package. The Fréchet ParticleNet Distance (FPND), which is the ParticleNet [54]-adaptation of the Fréchet inception distance [55] that is standard in computer vision; and coverage (COV) and minimum matching distance (MMD) which measure the ratio of samples in X (e.g. the generated jets) that have a match in Y (e.g. the input jets) and the average distance between matched samples, respectively, are also measured. Table 9 shows that among the models implemented in this work, the ConVAE+NF approach is the best in almost every metric. However, MPGAN outperforms the VAE-based approaches in every single metric. The advantage of the ConVAE+NF approach is that it is approximately two times faster: the average time to generate a single jet is $18.30 \pm 0.04 \mu\text{s}$ for ConVAE+NF versus $35.7 \mu\text{s}$ for MPGAN measured using an NVIDIA Tesla T4 GPU. Nevertheless, when compared with the EPiC-GAN model, which also achieves strong physics performance and can generate a single jet in $2 \mu\text{s}$, the ConVAE+NF model still lacks speed. It is still interesting to continue development of the latter; since the techniques applied in both models are completely distinct, one could expect that their strengths and weaknesses are complementary. Additionally, the availability of multiple tools for the same objective is usually expected by the HEP community.

From the comparisons of the low- and high-level jet feature distributions, we observe that the mixed ConVAE+NF approach exhibits an improvement over the ConVAE alone. We attribute this to two reasons: (1) the standard Gaussian distribution, used by the ConVAE alone but altered in the ConVAE+NF approach, is not the optimal probability distribution for the elements in the latent space dimension, and (2) the decompression of those values could be improved by using the same parameters of the ConVAE tuned for reconstruction. Still, there are discrepancies between the ConVAE+NF generated jets and input jets, mainly related to the substructure variables, which are not present for the MPGAN approach. Other than the structural distinction between GAN and VAE, one of the core differences between the two approaches is that the architecture for the MPGAN is a GNN. The representation of jet constituents as an unordered set of particles is more natural, intrinsically preserves permutation invariance, and most likely contributes to the differences between the ConVAE and MPGAN results.

6. Summary and outlook

We presented a novel technique in the context of hadronic jets generation in simulated high-energy pp collisions, based on a ML approach that combines a ConVAE with NFs. This method provides an opportunity to explore and enhance our capabilities for creating point-cloud objects in a broader context, with a particular emphasis on its potential application within the field of high energy physics. From the values of EMD_{sum} obtained, there was a clear improvement with respect to the work in [13], not only by the application of hyperparameter optimization to the ConVAE, but also with the usage of the ConVAE+NF technique. The generation of gluon jets was performed using the ConVAE+NF model and compared with baseline ConVAE and NF models alone, as well as the state-of-the-art MPGAN. The ConVAE+NF approach is superior to the first two, but needs further improvements to be comparable to the latter.

There is, however, an improvement in inference time compared to MPGAN as the ConVAE+NF can generate a jet twice as fast, but it still lacks speed to be comparable with EPiC-GAN. Even in the scenario where the ConVAE+NF is not the fastest network, it still offer advantages in physics applications where large amounts of simulated samples are needed but perfect accuracy is not a strict requirement, since the techniques used in each model are completely distinct and it can be expected their weak and strong characteristics to be complementary, specially in the HEP context where more than one method for the generation of new data is wanted. It is worth noting that the MPGAN architecture is based on a graph NN, which has a much more natural representation for a particle-based jet dataset. In future work, a graph-based VAE+NF can be implemented, trained, and tested to check for improvements in the jet generation capabilities and timing.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: [10.5281/zenodo.3601436](https://doi.org/10.5281/zenodo.3601436).

Acknowledgments

B O, J F, R C and T T are supported by Grant 2018/25225-9, São Paulo Research Foundation (FAPESP). B O was also partially supported by Grants 2019/16401-0 and 2020/06600-3, São Paulo Research Foundation (FAPESP). R C and T T were also partially supported by Grant 2022/02950-5, São Paulo Research Foundation (FAPESP). R K was partially supported by an IRIS-HEP fellowship through the U.S. National Science Foundation (NSF) under Cooperative Agreement OAC-1836650. R K was additionally supported by the LHC Physics Center at Fermi National Accelerator Laboratory, managed and operated by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy (DOE). J D is supported by the DOE, Office of Science, Office of High Energy Physics Early Career Research program under Award No. DE-SC0021187, the DOE, Office of Advanced Scientific Computing Research under Award No. DE-SC0021396 (FAIR4HEP), and the NSF HDR Institute for Accelerating AI Algorithms for Data Driven Discovery (A3D3) under Cooperative Agreement OAC-2117997. M P and M T were supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 772369). D G is partially supported by the EU ICT-48 2020 Project TAILOR (No. 952215).

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Appendix B

Generator Cards

In this appendix, the templates of the cards used to generate the signal MC samples for the search of disappearing tracks are displayed. Except for the customization card that needs to be specific for each chargino mass/lifetime, the other cards use the mass, lifetime, and $x_{Q_{\text{cut}}}$ as input to produce the samples.

B.1 Run Card

```
#####
#                               MadGraph5_aMC@NLO                               *
#                               *
#                               run_card.dat MadEvent                           *
#                               *
# This file is used to set the parameters of the run.                         *
#                               *
# Some notation/conventions:                                                  *
#                               *
# Lines starting with a '#' are info or comments                            *
#                               *
# mind the format:  value      = variable      ! comment                     *
#                               *
# To display more options, you can type the command:                        *
#   update full_run_card                                                       *
#####
#
#####
# Tag name for the run (one word)                                             *
#####
# tag_1      = run_tag ! name of the run
#####
# Number of events and rnd seed                                             *
# Warning: Do not generate more than 1M events in a single run              *
#####
# 10000 = nevents ! Number of unweighted events requested
# 0      = iseed   ! rnd seed (0=assigned automatically=default))
#####
# Collider type and energy                                                  *
# lpp: 0=No PDF, 1=proton, -1=antiproton, 2=photon from proton,              *
#      3=photon from electron, 4=photon from muon                          *
#####
```

```

1          = lpp1      ! beam 1 type
1          = lpp2      ! beam 2 type
6800.0     = ebeam1    ! beam 1 total energy in GeV
6800.0     = ebeam2    ! beam 2 total energy in GeV
# To see polarised beam options: type "update beam_pol"

#*****
# PDF CHOICE: this automatically fixes also alpha_s and its evol.      *
#*****
'lhpdf'     = pdlabel    ! PDF set
$DEFAULT_PDF_SETS = lhaid
$DEFAULT_PDF_MEMBERS = reweight_PDF
# To see heavy ion options: type "update ion_pdf"
#*****
# Renormalization and factorization scales                             *
#*****
False = fixed_ren_scale ! if .true. use fixed ren scale
False      = fixed_fac_scale ! if .true. use fixed fac scale
91.188 = scale           ! fixed ren scale
91.188 = dsqrt_q2fact1    ! fixed fact scale for pdf1
91.188 = dsqrt_q2fact2    ! fixed fact scale for pdf2
-1 = dynamical_scale_choice ! Choose one of the preselected dynamical choices
1.0 = scalefact           ! scale factor for event-by-event scales
#*****
# Type and output format
#*****
False      = gridpack !True = setting up the grid pack
1.0 = time_of_flight ! threshold (in mm) below which the invariant livetime is not written
(-1 means not written)
average = event_norm      ! average/sum. Normalization of the weight in the LHEF
#*****
# Matching parameter (MLM only)
#*****
1 = ickkw           ! 0 no matching, 1 MLM
1.0 = alpsfact       ! scale factor for QCD emission vx
False = chcluster    ! cluster only according to channel diag
4 = asrwtgflavor     ! highest quark flavor for a_s reweight
True  = auto_ptj_mjj ! Automatic setting of ptj and mjj if xqcut >0
                        ! (turn off for VBF and single top processes)
_XQCUT = xqcut       ! minimum kt jet measure between partons

#*****
# Turn on either the ktDurham or ptLund cut to activate                *
# CKKW(L) merging with Pythia8 [arXiv:1410.3012, arXiv:1109.4829]    *
#*****
-1.0 = ktDurham
0.4 = dparameter
-1.0 = ptLund
1, 2, 3, 4, 5, 6, 21, 1000001, 1000002, 1000003, 1000004, 1000005, 1000006, 1000021,
2000001, 2000002, 2000003, 2000004, 2000005, 2000006 = pdgs_for_merging_cut ! PDGs for
two cuts above

#*****
# Generation bias, check the wiki page below for more information:    *
# 'cp3.irmp.ucl.ac.be/projects/madgraph/wiki/LOEventGenerationBias' *

```

```

*****
None = bias_module ! Bias type of bias, [None, ptj_bias, -custom_folder-]
{} = bias_parameters ! Specifies the parameters of the module.
#
*****
# Parton level cuts definition *
*****
#
#
*****
# BW cutoff (M+/-bwcutoff*Gamma) ! Define on/off-shell for "$" and decay
*****
15.0 = bwcutoff ! (M+/-bwcutoff*Gamma)
*****
# Standard Cuts *
*****
# Minimum and maximum pt's (for max, -1 means no cut) *
*****
0.01 = ptj ! minimum pt for the jets
-1.0 = ptjmax ! maximum pt for the jets
{} = pt_min_pdg ! pt cut for other particles (use pdg code). Applied on particle and anti-particle
{} = pt_max_pdg ! pt cut for other particles (syntax e.g. {6: 100, 25: 50})
#
# For display option for energy cut in the partonic center of mass frame type 'update ecut'
#
*****
# Maximum and minimum absolute rapidity (for max, -1 means no cut) *
*****
5.0 = etaj ! max rap for the jets
{} = eta_min_pdg ! rap cut for other particles (use pdg code). Applied on particle and anti-particle
{} = eta_max_pdg ! rap cut for other particles (syntax e.g. {6: 2.5, 23: 5})
*****
# Minimum and maximum DeltaR distance *
*****
*****
# Minimum and maximum invariant mass for pairs *
*****
{} = mxx_min_pdg ! min invariant mass of a pair of particles X/X~ (e.g. {6:250})
{'default': False} = mxx_only_part_antipart ! if True the invariant mass is applied only
! to pairs of particle/antiparticle and not to pairs of the same pdg codes.
*****
# Inclusive cuts *
*****
0.0 = ptheavy ! minimum pt for at least one heavy final state
*****
# maximal pdg code for quark to be considered as a light jet *
# (otherwise b cuts are applied) *
*****
4 = maxjetflavor ! Maximum jet pdg code
*****
*****
# Store info for systematics studies *
# WARNING: Do not use for interference type of computation *
*****
True = use_syst ! Enable systematics studies

```

B.2 Process Card

```
import model MSSM_UFO

define x1 = x1+ x1-

generate p p > x1+ x1-
add process p p > x1 n1
add process p p > x1 n1 j
add process p p > x1+ x1- j

output FILENAME -nojpeg
```


B.3 Customize Card

```
set param_card sminputs 1 1.278425e+02
set param_card sminputs 3 1.172000e-01
set param_card sminputs 5 4.200000e+00
set param_card minpar 1 1.500000e+03
set param_card minpar 2 2.464400e+05
set param_card minpar 3 5.000000e+00
set param_card minpar 4 1.000000e+00
set param_card extpar 0 1.042289e+16
set param_card mass 1 5.040000e-03
set param_card mass 2 2.550000e-03
set param_card mass 3 1.010000e-01
set param_card mass 4 1.270000e+00
set param_card mass 5 4.200000e+00
set param_card mass 6 1.730700e+02
set param_card mass 11 5.110000e-04
set param_card mass 13 1.056600e-01
set param_card mass 15 1.777000e+00
set param_card mass 23 9.117000e+01
set param_card mass 24 8.042300e+01
set param_card mass 25 1.169188e+02
set param_card mass 35 4.139955e+03
set param_card mass 36 4.112712e+03
set param_card mass 37 4.127721e+03
set param_card mass 1000001 4.686348e+03
set param_card mass 1000002 4.685674e+03
set param_card mass 1000003 4.686348e+03
set param_card mass 1000004 4.685675e+03
set param_card mass 1000005 4.094006e+03
set param_card mass 1000006 3.409915e+03
set param_card mass 1000011 1.146789e+03
set param_card mass 1000012 1.125622e+03
set param_card mass 1000013 1.146789e+03
set param_card mass 1000014 1.125622e+03
set param_card mass 1000015 1.022276e+03
set param_card mass 1000016 1.112258e+03
set param_card mass 1000021 4.746731e+03
set param_card mass 1000022 6.998741e+02
set param_card mass 1000023 2.269050e+03
set param_card mass 1000024 7.000476e+02
set param_card mass 1000025 -3.871534e+03
set param_card mass 1000035 3.872823e+03
set param_card mass 1000037 3.877723e+03
set param_card mass 2000001 4.760781e+03
set param_card mass 2000002 4.716490e+03
set param_card mass 2000003 4.760781e+03
set param_card mass 2000004 4.716490e+03
set param_card mass 2000005 4.724744e+03
set param_card mass 2000006 4.132603e+03
set param_card mass 2000011 1.028006e+03
set param_card mass 2000013 1.028006e+03
set param_card mass 2000015 1.125748e+03
```

```
set param_card nmix 1 1 -8.253396e-04
set param_card nmix 1 2 9.997768e-01
set param_card nmix 1 3 -2.024051e-02
set param_card nmix 1 4 6.010189e-03
set param_card nmix 2 1 9.997944e-01
set param_card nmix 2 2 1.234040e-03
set param_card nmix 2 3 1.686326e-02
set param_card nmix 2 4 -1.119322e-02
set param_card nmix 3 1 -4.019827e-03
set param_card nmix 3 2 1.005844e-02
set param_card nmix 3 3 7.069792e-01
set param_card nmix 3 4 7.071513e-01
set param_card nmix 4 1 1.985802e-02
set param_card nmix 4 2 -1.854149e-02
set param_card nmix 4 3 -7.067434e-01
set param_card nmix 4 4 7.069480e-01
set param_card umix 1 1 -9.995645e-01
set param_card umix 1 2 2.950852e-02
set param_card umix 2 1 -2.950852e-02
set param_card umix 2 2 -9.995645e-01
set param_card vmix 1 1 -9.999370e-01
set param_card vmix 1 2 1.122527e-02
set param_card vmix 2 1 -1.122527e-02
set param_card vmix 2 2 -9.999370e-01
set param_card yu 3 3 8.388877e-01
set param_card yd 3 3 6.522101e-02
set param_card ye 3 3 5.158244e-02
set param_card hmix 1 3.875142e+03
set param_card hmix 2 5.000000e+00
set param_card hmix 4 1.691440e+07
set param_card msoft 1 2.303352e+03
set param_card msoft 2 6.642549e+02
set param_card msoft 3 -4.503769e+03
set param_card decay 6 1.508336e+00
set param_card decay 23 2.495200e+00
set param_card decay 24 2.085000e+00
set param_card decay 25 4.070000e-03
set param_card decay 1 0.000000e+00
set param_card decay 2 0.000000e+00
set param_card decay 3 0.000000e+00
set param_card decay 4 0.000000e+00
set param_card decay 5 0.000000e+00
set param_card decay 11 0.000000e+00
set param_card decay 12 0.000000e+00
set param_card decay 13 0.000000e+00
set param_card decay 14 0.000000e+00
set param_card decay 15 0.000000e+00
set param_card decay 16 0.000000e+00
set param_card decay 21 0.000000e+00
set param_card decay 22 0.000000e+00
set param_card decay 1000022 0.000000e+00
set param_card decay 1000024 WIDTH
set param_card decay 1000023 0.000000e+00
set param_card decay 1000025 1.915985e+00
set param_card decay 1000035 2.585851e+00
```

```
set param_card decay 1000037 2.486895e+00
set param_card decay 1000021 5.506754e+00
set param_card decay 35 5.748014e-01
set param_card decay 36 6.321785e-01
set param_card decay 37 5.469628e-01
set param_card decay 1000012 1.498816e-01
set param_card decay 1000014 1.498816e-01
set param_card decay 1000016 1.475190e-01
set param_card decay 1000011 2.136822e-01
set param_card decay 1000013 2.136822e-01
set param_card decay 1000015 1.483273e-01
set param_card decay 2000011 2.161216e-01
set param_card decay 2000013 2.161216e-01
set param_card decay 2000015 2.699061e-01
set param_card decay 1000002 5.477195e+00
set param_card decay 1000004 5.477195e+00
set param_card decay 1000006 2.021596e+00
set param_card decay 2000002 1.152973e+00
set param_card decay 2000004 1.152973e+00
set param_card decay 2000006 7.373133e+00
set param_card decay 1000001 5.312788e+00
set param_card decay 1000003 5.312788e+00
set param_card decay 1000005 3.736276e+00
set param_card decay 2000001 2.858123e-01
set param_card decay 2000003 2.858123e-01
set param_card decay 2000005 8.015663e-01
set param_card usqmix 1 1 1.000000e+00
set param_card usqmix 2 2 1.000000e+00
set param_card usqmix 4 4 1.000000e+00
set param_card usqmix 5 5 1.000000e+00
set param_card usqmix 3 3 8.360244e-02
set param_card usqmix 3 6 -9.964992e-01
set param_card usqmix 6 3 9.964992e-01
set param_card usqmix 6 6 8.360244e-02
set param_card dsqmix 1 1 1.000000e+00
set param_card dsqmix 2 2 1.000000e+00
set param_card dsqmix 4 4 1.000000e+00
set param_card dsqmix 5 5 1.000000e+00
set param_card dsqmix 3 3 9.999839e-01
set param_card dsqmix 3 6 5.668928e-03
set param_card dsqmix 6 3 -5.668928e-03
set param_card dsqmix 6 6 9.999839e-01
set param_card selmix 1 1 1.000000e+00
set param_card selmix 2 2 1.000000e+00
set param_card selmix 4 4 1.000000e+00
set param_card selmix 5 5 1.000000e+00
set param_card selmix 3 3 1.326595e-01
set param_card selmix 3 6 9.911616e-01
set param_card selmix 6 3 -9.911616e-01
set param_card selmix 6 6 1.326595e-01
set param_card vckm 1 1 1.000000e+00
set param_card vckm 2 2 1.000000e+00
set param_card vckm 3 3 1.000000e+00
set param_card snumix 1 1 1.000000e+00
set param_card snumix 2 2 1.000000e+00
```

```
set param_card snumix 3 3 1.000000e+00
set param_card upmns 1 1 1.000000e+00
set param_card upmns 2 2 1.000000e+00
set param_card upmns 3 3 1.000000e+00
set param_card te 1 1 2.576613e+03
set param_card te 2 2 2.576613e+03
set param_card te 3 3 1.329080e+02
set param_card tu 1 1 3.862562e+03
set param_card tu 2 2 3.862562e+03
set param_card tu 3 3 3.240256e+03
set param_card td 1 1 9.220798e+03
set param_card td 2 2 9.220798e+03
set param_card td 3 3 6.013898e+02
set param_card msl2 1 1 1.275231e+06
set param_card msl2 2 2 1.275231e+06
set param_card msl2 3 3 1.246026e+06
set param_card mse2 1 1 1.072075e+06
set param_card mse2 2 2 1.072075e+06
set param_card mse2 3 3 9.999359e+05
set param_card msq2 1 1 1.986683e+07
set param_card msq2 2 2 1.986683e+07
set param_card msq2 3 3 1.530788e+07
set param_card msu2 1 1 2.013590e+07
set param_card msu2 2 2 2.013590e+07
set param_card msu2 3 3 1.076281e+07
set param_card msd2 1 1 2.052692e+07
set param_card msd2 2 2 2.052692e+07
set param_card msd2 3 3 2.071235e+07
```

B.4 Hadronizer Parameters

```

generator = cms.EDFilter("Pythia8HadronizerFilter",
    pythiaPylistVerbosity = cms.untracked.int32(0),
    filterEfficiency = cms.untracked.double(-1),
    pythiaHepMCVerbosity = cms.untracked.bool(False),
    comEnergy = cms.double(COM_ENERGY),
    maxEventsToPrint = cms.untracked.int32(0),
    PythiaParameters = cms.PSet(
        pythia8CommonSettingsBlock,
        pythia8CP5SettingsBlock,
        pythia8PSweightsSettingsBlock,
        processParameters = cms.vstring(
            '1000024:isResonance = false',
            '1000024:oneChannel = 1 1.0 100 1000022 211',
            '1000024:tau0 = %.1f' % CTAU,
            'ParticleDecays:tau0Max = %.1f' % (CTAU * 10),
            'JetMatching:setMad = off',
            'JetMatching:scheme = 1',
            'JetMatching:merge = on',
            'JetMatching:jetAlgorithm = 2',
            'JetMatching:etaJetMax = 5.',
            'JetMatching:coneRadius = 1.',
            'JetMatching:slowJetPower = 1',
            'JetMatching:qCut = %.1f' % (XQCUT * 1.5), #this is the actual merging scale
            'JetMatching:nQmatch = 4', #4 corresponds to 4-flavour scheme (no matching of b-quarks),
            5 for 5-flavour scheme
            'JetMatching:nJetMax = 1', #number of partons in born matrix element for highest
            multiplicity
            'JetMatching:doShowerKt = off', #off for MLM matching, turn on for shower-kT matching
        ),
        parameterSets = cms.vstring(
            'pythia8CommonSettings',
            'pythia8CP5Settings',
            'pythia8PSweightsSettings',
            'processParameters'
        )
    ),
    # The following parameters are required by Exotica_HSCP_SIM_cfi:
    slhaFile = cms.untracked.string(''), # value not used
    processFile = cms.untracked.string('SimG4Core/CustomPhysics/data/RhadronProcessList.txt'),
    useregge = cms.bool(False),
    hscpFlavor = cms.untracked.string('stau'),
    massPoint = cms.untracked.int32(MCHI), # value not used
    particleFile = cms.untracked.string('DisappTrks/SignalMC/data/geant4/
    geant4_AMSB_chargino_%sGeV_ctau%scm.slha' % (MCHI, int(CTAU/10)))
)

```

Appendix C

Algorithms for Finding Missing Hits Corrections

C.1 Algorithm for Finding Missing Middle Hits Correction

Given a two-dimensional histogram, `uncorrectedMC`, of the number of hits in the strip detector vs. the number of missing middle hits filled using simulated background events and a probability to drop a single hit, `hitDropProbability`, the following procedure, `getCorrectedMC`, returns the expected distribution of missing middle hits.

```
Sub getExtraMissingMiddleHitsPDF (nHits, hitDropProbability)
  Book 1D histogram pdf
  For iToy = 0 to 10000
    missingMiddleHits = 0
    countMissingMiddleHits = False

    For iHit = 0 to nHits
      x = Random number in [0, 1)
      hit = x > hitDropProbability

      If not hit and countMissingMiddleHits Then
        missingMiddleHits = missingMiddleHits + 1
      Else If hit Then
        countMissingMiddleHits = True
      End If
    Next iHit
    pdf.Fill (missingMiddleHits)
  Next iToy

  Normalize histogram pdf

  Return pdf
End Sub

Sub getCorrectedMC (uncorrectedMC, hitDropProbability)
```

```

Book 1D histogram correctedMC
For nHits = 1 to 20
  extraMissingMiddleHitsPDF = getExtraMissingMiddleHitsPDF (nHits, hitDropProbability)

  For originalMissingMiddleHits = 0 to 6
    bin = uncorrectedMC.FindBin (originalMissingMiddleHits, nHits)
    nTracks = uncorrectedMC.GetBinContent (bin)

    For extraMissingMiddleHits = 0 to 6
      bin = extraMissingMiddleHitsPDF.FindBin (extraMissingMiddleHits)
      extraMissingMiddleHitProbability = extraMissingMiddleHitsPDF.GetBinContent (bin)

      missingMiddleHits = originalMissingMiddleHits + extraMissingMiddleHits
      bin = correctedMC.FindBin (missingMiddleHits)
      currentNTracks = correctedMC.GetBinContent (bin)

      correctedMC.SetBinContent (bin, currentNTracks + nTracks * extraMissingMiddleHitProbability)

    Next extraMissingMiddleHits
  Next originalMissingMiddleHits
Next nHits

Return correctedMC
End Sub

```

C.2 Algorithm for Finding Missing Outer Hits Corrections

Given a three-dimensional histogram, `uncorrectedMC`, of the number of hits in the strip detector vs. the number of hits in the TOB vs. the number of missing outer hits filled using simulated background events, a probability to drop a single hit, `hitDropProbability`, and a probability to drop every hit in the TOB, `tobDropProbability`, the following procedure, `getCorrectedMC`, returns the expected distribution of missing outer hits.

```

Sub getExtraMissingOuterHitsPDF (nHits, hitDropProbability)
  Book 1D histogram pdf
  For iToy = 0 to nToys
    missingOuterHits = 0
    For iHit = 0 to nHits
      x = Random number in [0, 1)
      hit = x > hitDropProbability

      If not hit Then
        missingOuterHits = missingOuterHits + 1
      Else
        Break
    End If
  Next iHit
  pdf.Fill (missingOuterHits)
Next iToy

Normalize histogram pdf

Return pdf
End Sub

Sub getCorrectedMC (uncorrectedMC, hitDropProbability, tobDropProbability, preOrPostTOB)
  Book 1D histogram correctedMC
  For nHits = 1 to 20
    extraMissingOuterHitsPDF = getExtraMissingOuterHitsPDF (nHits, hitDropProbability)
    For originalMissingOuterHits = 1 to 16
      For tobHits = 1 to 16
        bin = uncorrectedMC.FindBin (originalMissingOuterHits, tobHits, nHits)
        nTracks = uncorrectedMC.GetBinContent (bin)

        For extraMissingOuterHits = 0 to 16
          bin = extraMissingOuterHitsPDF.FindBin (extraMissingOuterHits)
          extraMissingOuterHitsProbability = extraMissingOuterHitsPDF.GetBinContent (bin)

          If preOrPostTOB = "PRE_TOB" Then
            missingOuterHits = originalMissingOuterHits + extraMissingOuterHits
            missingOuterHitsWithTOBDrop = originalMissingOuterHits + tobHits
          Else If preOrPostTOB = "POST_TOB" Then
            missingOuterHits = originalMissingOuterHits

```



```
        missingOuterHitsWithTOBDrop = originalMissingOuterHits + extraMissingOuterHits + tobHits
    End If

    bin = correctedMC.FindBin (missingOuterHits)
    currentNTracks = correctedMC.GetBinContent (bin)
    correctedMC.SetBinContent (bin, currentNTracks + nTracks \
        * extraMissingOuterHitsProbability * (1 - tobDropProbability))

    bin = correctedMC.FindBin (missingOuterHitsWithTOBDrop)
    currentNTracks = correctedMC.GetBinContent (bin)
    correctedMC.SetBinContent (bin, currentNTracks + nTracks \
        * extraMissingOuterHitsProbability * tobDropProbability)

    Next extraMissingOuterHits
    Next tobHits
    Next originalMissingOuterHits
Next nHits

Return correctedMC
End Sub
```

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