

Explorations of W Boson-Photon Scattering and Higgs-Scalar Resonance Production with the ATLAS Detector

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使用 ATLAS 探测器对 W 玻色子-光子散射和希格斯玻色子-标量粒子共振产生的研究

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ABSTRACT

The Standard Model provides a comprehensive theoretical framework for accurately describing fundamental particles and their interactions, including electromagnetic, weak, and strong interactions. The spontaneous breaking of electroweak symmetry through the Higgs mechanism explains the origin of particle masses, endowing the W and Z bosons with mass while ensuring that the photon remains massless. Vector Boson Scattering (VBS), as a key avenue for indirectly probing electroweak symmetry breaking, offers an opportunity for new physics searches through its sensitivity to quartic gauge boson couplings. The study of Higgs boson self-coupling and its interactions with other new particles is crucial for further understanding the completeness of the Higgs mechanism. The di-Higgs model and extended Higgs models provide the theoretical foundation for this research, facilitating the exploration of new physics phenomena and further revealing the complex nature of the Higgs boson.

The Large Hadron Collider (LHC) is the world's largest particle physics experiment platform, which, in 2012, enabled the discovery of the Higgs boson through the ATLAS (A Toroidal LHC Apparatus) and CMS (Compact Muon Solenoid) detectors, completing the final piece of the Standard Model. As one of the two largest multipurpose experiments at the LHC, the ATLAS detector plays a significant role not only in the search for new physics phenomena but also in the precise measurement of Standard Model processes. The detector consists of the inner detector, electromagnetic calorimeter, hadronic calorimeter, and muon spectrometer, with exceptional capabilities in electron, photon, muon, and jet reconstruction, allowing it to maintain high precision in a complex collision environment. The measurement of missing transverse momentum (E_T^{miss}) has been enhanced through finer energy calibration and improved background suppression techniques, improving the detection of neutrinos and other weakly interacting particles. Monte Carlo simulation techniques are essential in the ATLAS experiment, ensuring accurate comparisons between experimental data and theoretical predictions, thereby supporting the robustness of the physical analyses.

This thesis uses 140 fb^{-1} of data collected by the ATLAS detector at $\sqrt{s} = 13 \text{ TeV}$ from 2015 to 2018 and presents the first observation within the ATLAS collab-

oration of the electroweak production of a W boson and a photon in association with two jets, along with a differential cross-section measurement. The measurement is conducted in an enhanced VBS phase space to improve sensitivity to $WW\gamma\gamma$ couplings. The process demonstrates high sensitivity to quartic gauge boson couplings through the vector boson scattering mechanism, providing a stringent experimental test for electroweak symmetry breaking in the Standard Model. The event selection requires one electron or muon, missing transverse momentum, at least one photon, and two jets. The use of neural network-based multivariate techniques significantly improves the discrimination between electroweak $W\gamma jj$ production and the background. Complex and diverse background estimation is a major challenge in this analysis, with data-driven methods used to accurately estimate and analyze errors for fake photons from mis-reconstructed jets, electrons, or muons, as well as background from pile-up vertices. After combining theoretical and experimental uncertainties, the observed significance of the electroweak $W\gamma jj$ process exceeds 6 standard deviations, consistent with the expected significance of 6.3 standard deviations. The fiducial and differential cross sections are measured in a fiducial phase space close to the detector acceptance, with results that are consistent within uncertainties with leading-order Standard Model predictions from MadGraph5+Pythia8 and Sherpa. These results are used to constrain new physics effects based on effective field theory (EFT). This result is utilized to constrain new physics effects based on effective field theory, revealing that p_T^{jj} is the observable most sensitive to tensor operators, while p_T^l is the observable most sensitive to mixed scalar operators. Notably, the constraints on the f_{T3} and f_{T4} operators represent the first results published at the LHC.

The second physics analysis in this thesis is a search for a resonance decaying into a scalar particle and a Higgs boson in the final state with two bottom quarks and two photons, specifically investigating the process $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$. This analysis is also based on 140 fb^{-1} of data collected by the ATLAS detector at $\sqrt{s} = 13 \text{ TeV}$, covering the X mass range from 170 GeV to 1000 GeV and the S mass range from 15 GeV to 500 GeV. Due to the boosted S particle decaying into two b quarks, often reconstructed as a single b quark, the analysis is divided into two categories: 2 b -tagged and 1 b -tagged, corresponding to the recon-

struction of two and one b quarks, respectively. High-performance parameterised neural networks enhance signal purity, and in the 2 b -tagged category, interpolation techniques based on Lorentz transformations enable continuous sensitivity measurements across the (m_X, m_S) plane, optimizing the signal-to-background ratio across different parameter spaces. Although no significant excess over the background expectation is observed, upper limits on the product of the signal cross-section and branching ratio at each mass point were set by the analysis at the 95% confidence level, ranging from 39 fb to 0.09 fb. The most significant deviation occurs at $(m_X, m_S) = (575, 200)$ GeV, with a local significance of 3.5 standard deviations and a global significance of 2.0 standard deviations. For the $(m_X, m_S) = (650, 90)$ GeV mass point, CMS previously reported a local (global) significance of 3.8 (below 2.8) standard deviations for an excess, while this analysis shows consistency with the background-only hypothesis and set an upper limit of 0.2 fb on the signal cross-section at 95% CL.

Keywords: ATLAS Experiment, Standard Model, Vector boson scattering, Resonance decay, Scalar particle, Higgs boson, Physics beyond the Standard Model

摘要

标准模型提供了一个全面的理论框架，准确描述基本粒子及其相互作用，包括电磁相互作用、弱相互作用和强相互作用。电弱对称性自发破缺通过希格斯机制解释了粒子的质量起源，使 W 和 Z 玻色子获得质量，同时确保光子的质量保持为零。矢量玻色子散射 (Vector Boson Scattering, VBS) 作为间接探测电弱对称性破缺的关键途径，其四次规范玻色子耦合过程对新物理的探索提供了契机。研究希格斯粒子的自耦合及其与其他新粒子的耦合对于进一步理解希格斯机制的完整性至关重要，双希格斯以及扩展希格斯模型为这一研究提供了理论基础，有助于探索新物理现象并深入揭示希格斯粒子的复杂性质。

大型强子对撞机 (LHC) 是世界上最大的粒子物理实验平台，2012 年，通过 ATLAS (超环面仪器) 和 CMS (紧凑型缪子线圈) 探测器实现了希格斯玻色子的发现，完成了标准模型的最后一块拼图。作为 LHC 上两个最大的多功能实验之一，ATLAS 探测器不仅在新物理现象的探索中发挥了重要作用，还在标准模型过程的精确测量中具有关键地位。该探测器由内探测器、电磁量能器、强子量能器和缪子谱仪组成，具备卓越的电子、光子、缪子和喷注重建能力，使其在复杂的碰撞环境中保持高度精确。缺失横动量 (E_T^{miss}) 的测量通过更精细的能量标定和改进的背景抑制技术得到了增强，从而提高了对中微子和其他弱相互作用粒子的探测能力。蒙特卡洛模拟技术在 ATLAS 实验中至关重要，确保实验数据与理论预测之间的精确对比，从而提供了物理分析的可靠性。

本论文基于 2015 年至 2018 年间 LHC 上由 ATLAS 探测器采集的质心系能量为 $\sqrt{s} = 13$ TeV、总积分亮度为 140 fb^{-1} 的数据，首次在 ATLAS 合作组内观测到伴随两喷注的 W 玻色子和光子的电弱产生过程，并进行了微分截面测量。测量在增强的 VBS 相空间内进行，以提高对 $WW\gamma\gamma$ 耦合的敏感性。该过程通过矢量玻色子散射机制对四重规范玻色子耦合展现出高度敏感性，为验证标准模型中的电弱对称性破缺提供了严格的实验检验。事件选择要求包括一个电子或缪子、缺失的横动量、至少一个光子以及两个喷注。通过神经网络多变量技术，显著提升了电弱 $W\gamma jj$ 过程与背景的区分能力。复杂多样的背景估计是该物理分析中的一大挑战，通过采用数据驱动方法分别对喷注误重建为光子、电子或缪子，电子误重建为光子，以及来自多重堆积顶点的背景进行了精确估计和误差分析。综合理论与实验误差后，观测到的电弱 $W\gamma jj$ 过程的显著性远超过 6 个标准差，与预期的 6.3 个标准差一致。在接近探测器接受度的保形相空间中测量了保形截面和微分截面，结果与来自 MadGraph5+Pythia8 和 Sherpa 的标准模型

领头阶预测在误差范围内一致。该结果用于对基于有效场论的新物理效应进行约束,发现 p_T^{jj} 是对张量型算符最敏感的观测量,而 p_T^l 是对混合标量算符最敏感的观测量,其中对 f_{T3} 和 f_{T4} 算符的限制是 LHC 上首次发表的结果。

本论文的第二个物理分析是寻找一种共振衰变为标量粒子和希格斯玻色子的过程,末态包含两个底夸克和两个光子,具体研究过程为 $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$ 。该分析同样基于 ATLAS 探测器在 $\sqrt{s} = 13$ TeV 下采集的 140 fb^{-1} 的数据,研究覆盖了 X 质量范围 170 GeV 至 1000 GeV,以及 S 质量范围 15 GeV 至 500 GeV。由于增强 S 粒子衰变的 2 个 b 夸克常被重建为 1 个 b 夸克,因此研究分为 2 b -tagged 和 1 b -tagged 两个类别,分别对应重建 2 个和 1 个 b 夸克。通过高性能参数化神经网络来提升信号纯度,并在 2 b -tagged 类别中通过基于洛伦兹变换的插值技术实现了在 (m_X, m_S) 平面上连续的灵敏度测量,从而优化了不同参数空间内的信号与背景比。尽管未观察到显著超过背景预期的信号,分析仍在 95% 置信水平下对每个质量点处信号的截面与分支比乘积设定了上限,范围为 39 fb 至 0.09 fb。最显著的偏差出现在 $(m_X, m_S) = (575, 200)$ GeV 处,其局部显著性为 3.5 个标准差,全局显著性为 2.0 个标准差。对于 $(m_X, m_S) = (650, 90)$ GeV 的质量点, CMS 曾报告局部(全局)显著性为 3.8(低于 2.8)个标准差的超出,而此分析与仅背景假设吻合良好,并在 95% CL 下对信号截面设定了 0.2 fb 的上限。

关键字: ATLAS 实验, 标准模型, 矢量玻色子散射, 共振衰变, 标量粒子, 希格斯玻色子, 超越标准模型的物理学

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CHAPTER 1

Introduction

Particle physics has experienced substantial progress since the early 20th century, driven by the pursuit of understanding the fundamental constituents of matter and the fundamental forces governing their interactions. The Standard Model (SM) of particle physics, developed during the 1960s and 1970s, represents a remarkable achievement in both theoretical and experimental domains. It effectively describes the electromagnetic, weak, and strong interactions between fundamental particles within the framework of quantum field theory (QFT) [34, 35, 36]. Electroweak symmetry breaking, facilitated by the Higgs mechanism, accounts for the mass generation of the weak gauge bosons [37, 38, 39].

Despite its accomplishments, the SM is recognized as incomplete. It does not incorporate gravitational interactions, fails to account for dark matter and dark energy, which together make up a significant portion of the universe [40, 41], and does not adequately explain the observed baryon asymmetry in the universe [42]. These shortcomings, along with unresolved theoretical challenges such as the hierarchy problem, have spurred investigations into new physics beyond the Standard Model (BSM). Such phenomena are anticipated to emerge either at higher energy scales or through high-precision measurements that could uncover subtle deviations from SM predictions [43].

To explore these frontiers, the Large Hadron Collider (LHC) at CERN was established as the most powerful particle accelerator in existence. With a center-of-mass energy reaching up to 13 TeV, the LHC facilitates the investigation of energy scales far exceeding those previously accessible [44]. The ATLAS experiment, one of the four principal experiments at the LHC, is a versatile detector designed to investigate a broad spectrum of phenomena, ranging from precise measurements of SM processes to the potential discovery of new BSM physics [45].

The ATLAS detector's capacity for high-precision particle reconstruction and identification is critical for these investigations. Particle identification and reconstruction rely on sophisticated algorithms that process the data acquired from various detector components, including the inner detector, calorimeters, and muon

spectrometer. Accurate reconstruction of particles such as electrons, photons, muons, jets, and the measurement of missing transverse energy is vital for analyzing the results of LHC collisions [46].

Monte Carlo (MC) simulations are widely employed in particle physics to model the anticipated behavior of particles. These simulations are essential for understanding detector responses, optimizing experimental designs and operations, and for comparing experimental data with theoretical predictions. Within the ATLAS framework, MC simulations generate events that reproduce the collisions recorded by the detector, enabling comprehensive analyses of both background processes and potential signals [47].

This thesis presents two primary physics analyses utilizing data from the ATLAS experiment. The first analysis searches vector boson scattering (VBS) in the $W\gamma jj$ final state, serving as a stringent test of the SM. VBS processes are particularly sensitive to the electroweak sector and are noteworthy because they encompass the self-interaction of gauge bosons, a distinctive prediction of the SM. Precise measurements of VBS can validate the SM and may uncover indications of new physics through deviations from expected cross-sections [48, 49].

The second analysis explores the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ process, where X denotes a heavy scalar or pseudoscalar particle, S represents a lighter scalar, and H corresponds to the SM-like Higgs boson. This decay chain is motivated by various BSM theories that expand the Higgs sector by introducing additional scalar fields. The $b\bar{b}\gamma\gamma$ final state is particularly advantageous due to the large branching ratio of $S \rightarrow b\bar{b}$ and the clean experimental signature of $H \rightarrow \gamma\gamma$. Analyzing this process offers a promising path for discovering new physics and gaining insights into the nature of the Higgs sector beyond the SM [50, 51].

In summary, the work presented in this thesis contributes to the ongoing efforts to test the SM's predictions and search for BSM physics using data from the ATLAS experiment at the LHC. Additionally, the appendix covers the R&D of large-area Glass Resistive Plate Chambers (GRPC) and the data quality studies of the ATLAS RPC Detector Control System (DCS).

CHAPTER 2

The Standard Model and New Physics Beyond the Standard Model

The discovery of the Higgs boson at CERN in 2012 marked the completion of the experimental verification of the Standard Model (SM) particle spectrum. While the potential for discovering new physics exists within the scope of the Large Hadron Collider (LHC) or its forthcoming successor experiments, there remains the likelihood that the masses of particles beyond those predicted by the SM could lie significantly outside the energy range accessible to any anticipated particle collider.

Yukawa’s prediction of a new particle in the mid-1930s, followed by the discoveries of the muon and pion, signified the beginning of a foundational period in particle physics, ultimately leading to the observation of the Higgs boson. Significant theoretical advancements in nuclear physics and quantum electrodynamics throughout the 1930s concentrated on the analysis of scattering amplitudes in many-body systems [52]. These studies revealed that anomalously large scattering cross sections result from resonance phenomena, attributed to the production of on-shell intermediate particles that enhance the cross sections during interactions. As a result, the quest for resonances—manifested as peaks in the graphical representation of the ratio between the particle cross sections and their total energy—became the standard approach for the discovery of new particles in accelerator experiments.

The first particle identified in an accelerator was the neutral pion in 1950 [53]. Following this discovery, the field of particle physics progressed rapidly, particularly during the 1950s, with the identification of numerous hadrons initially classified as elementary particles. This “particle zoo” prompted physicists to investigate the potential existence of more fundamental constituents of matter, leading to theoretical predictions of particles such as gluons, quarks, tau leptons, the Higgs boson, and the W and Z gauge bosons. These advancements culminated in the establishment of the Standard Model, whose representation (Figure 2.1) has be-

come definitive in modern physics, fundamentally structured by the principles of particle interactions and symmetries [54].

In the Standard Model (SM), bosons function as force carriers, while fermions are categorized by their flavors—a classification introduced in the 1960s to differentiate among families of particles with analogous properties, referred to as generations of matter. Both bosons and fermions are recognized as fundamental particles and are represented theoretically as such.

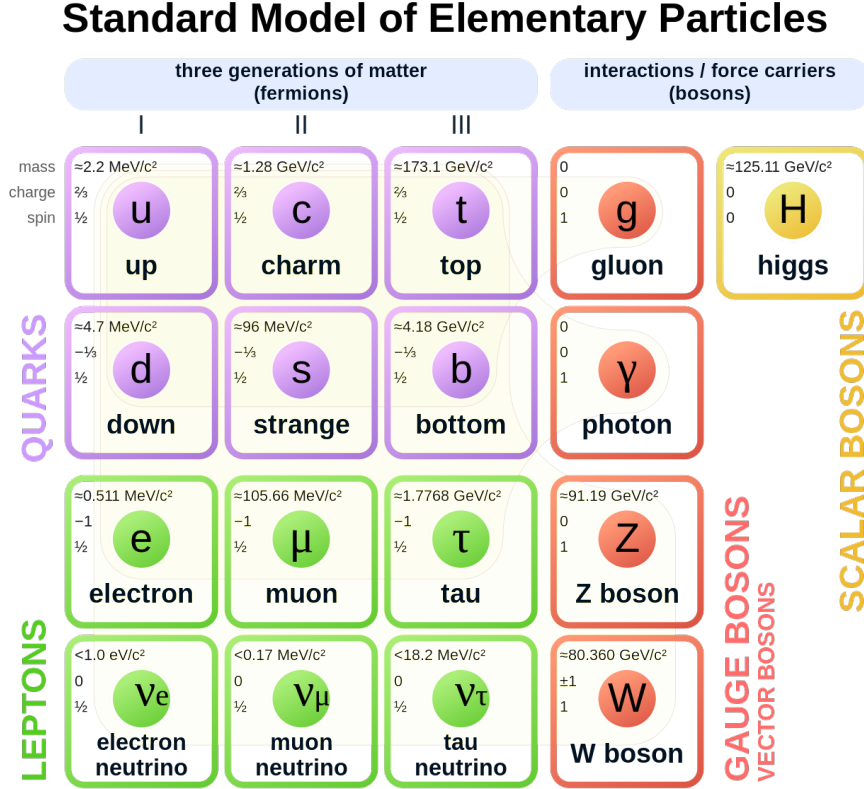


Fig. 2.1: The Standard Model of elementary particles (source: Wikimedia Commons/Fermilab, U.S. Department of Energy Office of Science, Particle Data Group)

The current formulation of the Standard Model (SM) was established in the mid-1970s with the confirmation of quark existence through deep inelastic scattering experiments—an advancement of the Rutherford scattering technique at higher energies used to investigate the substructure of hadrons [55]. Since that time, the SM has played a pivotal role in the pursuit of comprehensive validation. The discovery of the W and Z bosons in the early 1980s, the top quark in the mid-1990s, and the Higgs boson in 2012 represent some of the most significant experimental milestones in contemporary particle physics [56, 57, 58, 59, 60, 61, 62, 63].

This marked the decline of accidental discoveries of fundamental particles, a period which, remarkably, led to the construction of powerful new accelerators

and experiments requiring significant technical, human, and financial resources. Today, this raises questions about our capacity to achieve even higher energies to discover new particles.

The SM remains the most comprehensive theory describing elementary particles and their interactions. It can be understood as a generalization of quantum electrodynamics, extending the structure of interactions from Abelian to non-Abelian gauge theories. In addition to the photon mediating electromagnetic interactions, the SM includes W and Z bosons responsible for electroweak interactions and gluons for strong interactions. However, the SM is not considered a “final” theory, especially since it does not account for gravity, the fourth fundamental interaction. Thus, it is anticipated that “new physics” remains to be discovered, continuing the historical evolution described so far. An analysis of the SM’s limitations and proposed extensions may provide a glimpse of future discoveries.

The SM depends on 19 parameters that describe the properties of fundamental particles/fields [64], with their numerical values determined through measurements: three gauge couplings, the masses of the three charged leptons and six quarks, the Higgs mass and self-coupling, four quark mixing parameters, and the θ -parameter governing CP violation in the strong sector (neutrino masses are assumed to be zero in the SM). Once these parameters are fixed, they allow for theoretical predictions of other observables. Comparing these predictions to experimental data provides consistency checks on the SM. Two essential plots from these measurements are shown in Figure 2.2. The left plot shows the electroweak fit, illustrating how SM-derived theoretical expectations match electroweak precision data. The right plot shows the unitarity triangle, a graphical representation of the Cabibbo-Kobayashi-Maskawa matrix, which provides information on the flavor-changing weak interaction’s strength. The absence of significant tension in over-constraining SM parameters from these plots indicates no evident hint of physics beyond the Standard Model (BSM).

Physics at all mass scales M influences measurements conducted at a specific energy E . Consequently, precision tests of the SM not only assess its internal consistency but also serve as indirect probes of BSM physics at the associated mass scale M_{BSM} . However, BSM effects in these precision measurements are generally suppressed by factors proportional to $(E/M_{BSM})^n$, with n dependent on the interactions and particles involved. Therefore, the sensitivity of such precision tests to BSM phenomena is closely tied to experimental uncertainties. This sensitivity is particularly evident in well-defined BSM frameworks like the Minimal Supersymmetric Standard Model (MSSM) [65], where current experimental constraints place lower bounds on M_{BSM} just beyond a few TeV. Despite the suppression by

the E/M_{BSM} ratio, precision measurements remain a valuable tool for probing the energy frontier of BSM physics.

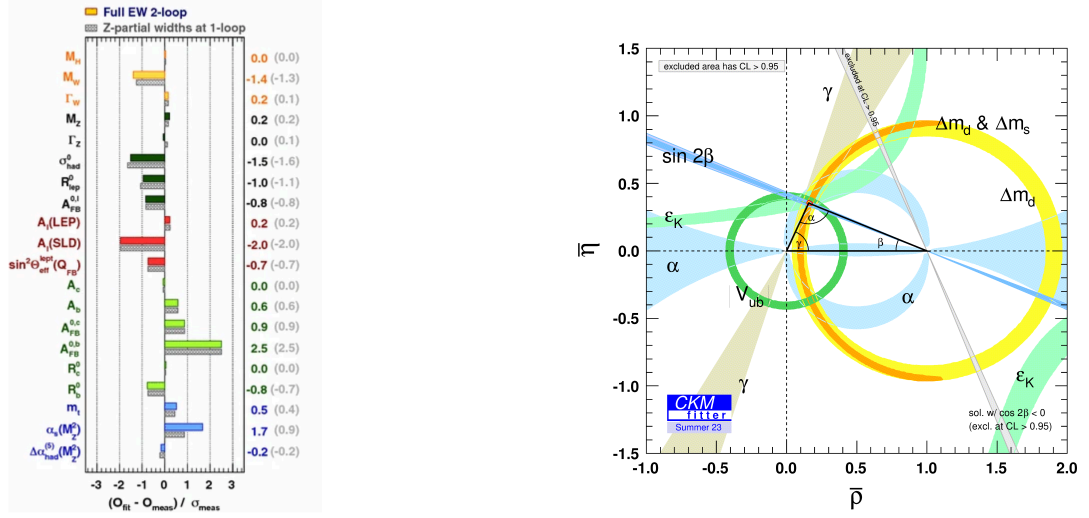


Fig. 2.2: The electroweak fit as shown in [1] and the unitarity triangle discussed in [2]

2.1 The Standard Model

2.1.1 Theoretical Foundations

The Standard Model (SM) of particle physics stands as a cornerstone in our understanding of the fundamental constituents and interactions in the universe, excluding gravitation. This theoretical framework delineates the electromagnetic, weak, and strong nuclear forces, which govern the dynamics of subatomic particles. It categorically organizes elementary particles into quarks, leptons, and gauge bosons—the force carriers mediating interactions among the matter particles.

The evolution of the SM is a narrative of the cumulative progress in physics over the 20th century, marked by crucial theoretical insights and significant experimental discoveries. The inception of Quantum Electrodynamics (QED) in the 1940s, pioneered by Feynman, Schwinger, and Tomonaga, was the first step toward the SM, elucidating the quantum nature of electromagnetic interactions. The subsequent formulation of the electroweak theory by Glashow, Weinberg, and Salam unified the electromagnetic and weak forces, predicting the existence of the W and Z bosons, which were experimentally confirmed at CERN in the early 1980s [66, 67, 68]. In parallel, the development of Quantum Chromodynamics (QCD) in the 1970s by Gross, Politzer, and Wilczek provided a comprehensive framework for understanding the strong nuclear force, characterizing the interac-

tions between quarks and gluons.

The SM's mathematical foundation is encapsulated in a Lagrangian formulation, where forces are depicted by gauge fields with the symmetry group $\mathcal{G} = SU(2)_L \otimes U(1)_Y \otimes SU(3)_C$, corresponding to weak isospin, hypercharge, and color charge quantum numbers, respectively. Matter is represented by spin- $\frac{1}{2}$ fields, organized into three families of quarks and leptons. Quarks are triplets under $SU(3)_C$, while leptons are singlets, and each family is further subdivided into doublets. Within each doublet, particles differ by their electric charge, encompassing up- and down-type quarks (u, d), neutrinos, and charged leptons (ν, ℓ). Notably, only left-handed doublets are charged under $SU(2)_L$, making gauge interactions in the SM chiral.

A significant challenge in the SM is the origin of the masses of gauge bosons and fermions, as the inclusion of mass terms in the Lagrangian inherently breaks gauge symmetries. This issue was resolved in the 1960s through the introduction of a scalar field, known as the Higgs field, by Higgs, Brout, Englert, Guralnik, Hagen, and Kibble [69, 70, 71, 72, 73, 74]. The addition of this scalar field facilitates spontaneous Electroweak Symmetry Breaking (EWSB), providing mass to the gauge fields while maintaining gauge symmetries. After EWSB, the hypercharge and isospin fields combine, giving rise to the mediators of the electromagnetic and weak interactions: the massless photon (γ) and the massive weak bosons ($W^\pm, Z$). Similarly, Yukawa-type interactions between the scalar field and fermions generate fermion masses [67]. The scalar field's quantum, the Higgs boson, predicted by the SM, was empirically confirmed in 2012 by the ATLAS and CMS collaborations at CERN, nearly fifty years after its theoretical proposal.

The primary significance of the SM lies in its exceptional predictive power and empirical validation through countless experiments, making it a cornerstone in the study of fundamental physics.

2.1.2 Electroweak Interaction

The Electroweak Lagrangian, $\mathcal{L}_{\text{EW}}$, encapsulates the interactions among fermions (quarks and leptons) and gauge bosons ($W^\pm, Z^0$, and γ). It is a cornerstone of the Standard Model, describing the unification of electromagnetic and weak forces. The Lagrangian can be decomposed into several parts:

$$\mathcal{L}_{\text{EW}} = \mathcal{L}_{\text{gauge}} + \mathcal{L}_{\text{fermion}} + \mathcal{L}_{\text{Higgs}} + \mathcal{L}_{\text{Yukawa}} \quad (2.1)$$

where,

- $\mathcal{L}_{\text{gauge}}$ represents the kinetic energy of the gauge bosons and their self-interactions.

- $\mathcal{L}_{\text{fermion}}$ includes the interactions between fermions and gauge bosons.
- $\mathcal{L}_{\text{Higgs}}$ describes the dynamics of the Higgs field, including its potential.
- $\mathcal{L}_{\text{Yukawa}}$ covers the interactions between the Higgs field and fermions, giving rise to fermion masses.

Gauge Boson Kinetic Terms

The kinetic terms for the gauge bosons are expressed through the field strength tensors for the $SU(2)_L$ and $U(1)_Y$ gauge fields:

$$\mathcal{L}_{\text{gauge}} = -\frac{1}{4}W_{\mu\nu}^a W^{a\mu\nu} - \frac{1}{4}B_{\mu\nu}B^{\mu\nu}, \quad (2.2)$$

where $W_{\mu\nu}^a$ and $B_{\mu\nu}$ represent the field strength tensors of the $SU(2)_L$ and $U(1)_Y$ gauge fields, respectively.

Higgs Mechanism and Mass Generation

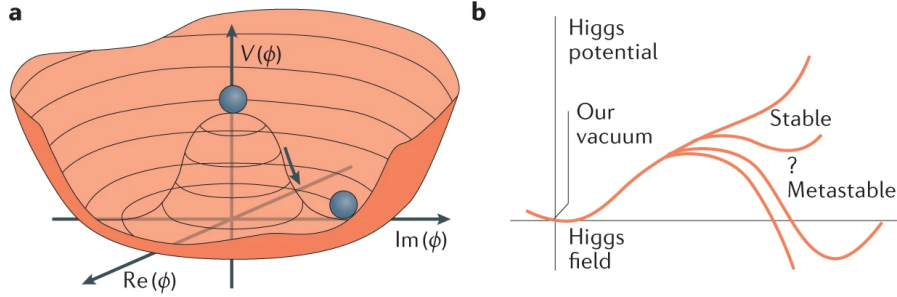


Fig. 2.3: Panel (a) shows the Higgs potential $V(\phi)$ for a scalar field ϕ with a mass parameter $\mu^2 < 0$, demonstrating the spontaneous breaking of the rotational $U(1)$ symmetry. The points at the minimum of the potential represent the spontaneous breaking of electroweak symmetry, with $|\phi| = v/\sqrt{2}$ and $v \approx 246$ GeV. Panel (b) illustrates how quantum corrections can modify the Higgs potential, possibly introducing a secondary minimum and influencing vacuum metastability [3].

$$V(\Phi) = \mu^2 \Phi^\dagger \Phi + \lambda (\Phi^\dagger \Phi)^2, \quad (2.3)$$

where Φ denotes the Higgs doublet. This potential leads to spontaneous symmetry breaking, which, in turn, generates masses for the $W^\pm$ and Z^0 bosons. The specific derivation of the mass terms follows:

Given the Higgs field doublet, $\Phi = \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ v + h(x) \end{pmatrix}$, and substituting into the kinetic term, $|D_\mu \Phi|^2$, we arrive at mass terms for the gauge bosons:

$$\mathcal{L}_{\text{mass}} = \frac{g^2 v^2}{4} W_\mu^+ W^{\mu-} + \frac{v^2}{8} (g^2 W_\mu^3 W^{\mu3} + g'^2 B_\mu B^\mu - 2gg' W_\mu^3 B^\mu). \quad (2.4)$$

From which we derive the masses of the $W^\pm$ and Z^0 bosons:

$$m_W = \frac{gv}{2}, \quad (2.5)$$

$$m_Z = \frac{v}{2} \sqrt{g^2 + g'^2}. \quad (2.6)$$

Yukawa Interactions

Yukawa interactions, responsible for the masses of fermions, are given by:

$$\mathcal{L}_{\text{Yukawa}} = - \sum_f y_f (\bar{\Psi}_L \Phi \Psi_R + \text{h.c.}), \quad (2.7)$$

where y_f are the Yukawa coupling constants for fermions, indicating interactions between the Higgs field, and the left-handed and right-handed fermion fields, respectively. The Hermitian conjugate ensures the Lagrangian remains Hermitian, preserving quantum mechanical principles.

This comprehensive analysis elucidates the intricate structure of the Electroweak Lagrangian, showcasing the elegant unification of electromagnetic and weak interactions, the mechanism of mass generation through the Higgs field, and the fundamental interactions between fermions and gauge bosons within the framework of the Standard Model of particle physics.

2.1.3 Strong Interaction

The strong interaction is one of the four fundamental forces of nature, responsible for binding quarks and gluons within nucleons and nuclei. It is described by Quantum Chromodynamics (QCD), a non-abelian gauge theory based on the $SU(3)_C$ symmetry group.

2.1.4 Asymptotic Freedom

A hallmark of QCD is asymptotic freedom, which suggests that the strength of the strong interaction decreases as the energy scale increases or equivalently, as the distance between interacting particles decreases. This behavior is quantitatively described by the QCD beta function:

$$\beta(\alpha_s) = - \left(11 - \frac{2}{3}N_f \right) \frac{\alpha_s^2}{2\pi}, \quad (2.8)$$

where α_s is the strong coupling constant, and N_f is the number of quark flavors. This equation illustrates how QCD predicts quarks behave almost as free particles at high energies due to the anti-screening effect of gluon interactions.

2.1.5 QCD Lagrangian

The QCD Lagrangian encapsulates the dynamics of quarks and gluons. It is constructed to be invariant under $SU(3)_C$ local gauge transformations, which leads to the introduction of gluon fields that mediate the strong force. The Lagrangian is expressed as:

$$\mathcal{L}_{\text{QCD}} = -\frac{1}{4}G_{\mu\nu}^a G_a^{\mu\nu} + \sum_{f=1}^{N_f} \bar{\psi}_f (i\gamma^\mu D_\mu - m_f) \psi_f, \quad (2.9)$$

where $G_{\mu\nu}^a$ is the gluon field strength tensor, defined by:

$$G_{\mu\nu}^a = \partial_\mu A_\nu^a - \partial_\nu A_\mu^a + g_s f^{abc} A_\mu^b A_\nu^c, \quad (2.10)$$

A_μ^a are the gluon fields, g_s is the strong coupling constant, f^{abc} are the structure constants of $SU(3)_C$, ψ_f represents the quark fields, m_f their masses, and D_μ is the covariant derivative:

$$D_\mu = \partial_\mu - ig_s A_\mu^a T^a. \quad (2.11)$$

Here, T^a are the generators of the $SU(3)_C$ group, satisfying the commutation relation $[T^a, T^b] = if^{abc}T^c$.

The non-linear term $g_s f^{abc} A_\mu^b A_\nu^c$ in the field strength tensor $G_{\mu\nu}^a$ leads to the self-interaction of gluons, a unique feature of QCD. These self-interactions are responsible for the confining potential that binds quarks within hadrons and for asymptotic freedom.

2.2 Higgs boson production and decay mechanisms

2.2.1 Production mechanisms at hadron colliders

Extensive analyses of the Standard Model (SM) Higgs boson properties, with particular focus on the implications of loop corrections to decay rates and cross sections, are well-documented in the literature [75, 29, 30, 5, 6]. This section encapsulates the key findings.

At the Tevatron and LHC, the predominant Higgs boson production processes include gluon fusion (ggF), weak-boson fusion (VBF), associated production with a gauge boson (VH), and top-quark-associated production, both with a $t\bar{t}$ pair (ttH) and with a single top quark (tHq). These mechanisms are illustrated in Figure 2.4.

The production cross sections of the SM Higgs boson as a function of the center-of-mass energy $\sqrt{s}$ in proton-proton (pp) collisions, along with bands representing theoretical uncertainties, are illustrated in Figure 2.5 (left) [76]. An in-depth analysis of the uncertainties in theoretical predictions, arising from the omission of higher-order corrections and experimental uncertainties in the determination of Standard Model parameters, is discussed in Refs. [29, 30, 5, 6]. These studies also provide comprehensive discussions on the impact of uncertainties associated with parton distribution functions (PDFs), variations in QCD scales, and the procedures used to incorporate higher-order corrections in parton shower simulations. Additionally, the uncertainties arising from hadronization and parton shower events are also considered.

Table 2.1 provides a summary of the production cross sections and corresponding relative uncertainties for a Higgs boson mass of 125 GeV, across a range of $\sqrt{s}$ values: 7, 8, 13, 13.6, and 14 TeV.

Table 2.1: The production cross sections of the SM Higgs boson for $m_H = 125$ GeV in pp collisions (and in $p\bar{p}$ collisions at $\sqrt{s} = 1.96$ TeV for the Tevatron) are shown as a function of the center-of-mass energy, $\sqrt{s}$. The predictions for LHC energies are sourced from Refs. [29, 30, 5, 6, 4], while those for the Tevatron are based on Ref. [31]. The ggF channel predictions at the LHC incorporate the most recent N3LO QCD + NLO EW calculations. Uncertainty estimates assume no correlation between α_S and PDF uncertainties, with the total cross section uncertainties being primarily driven by those in the gluon fusion process.

$\sqrt{s}$ (TeV)	ggF	VBF	WH	ZH	ttH	total
1.96	$0.95^{+17\%}_{-17\%}$	$0.065^{+8\%}_{-7\%}$	$0.13^{+8\%}_{-8\%}$	$0.079^{+8\%}_{-8\%}$	$0.004^{+10\%}_{-10\%}$	$1.23^{+15\%}_{-15\%}$
7	$16.9^{+5.5\%}_{-7.6\%}$	$1.24^{+2.2\%}_{-2.2\%}$	$0.58^{+2.2\%}_{-2.3\%}$	$0.34^{+3.1\%}_{-3.0\%}$	$0.09^{+5.6\%}_{-10.2\%}$	$19.1^{+5\%}_{-7\%}$
8	$21.4^{+5.4\%}_{-7.6\%}$	$1.60^{+2.1\%}_{-2.1\%}$	$0.70^{+2.1\%}_{-2.2\%}$	$0.42^{+3.4\%}_{-2.9\%}$	$0.13^{+5.9\%}_{-10.1\%}$	$24.2^{+5\%}_{-7\%}$
13	$48.6^{+5.6\%}_{-7.4\%}$	$3.78^{+2.0\%}_{-2.1\%}$	$1.37^{+2.0\%}_{-2.0\%}$	$0.88^{+4.1\%}_{-3.5\%}$	$0.50^{+6.8\%}_{-9.9\%}$	$55.1^{+5\%}_{-7\%}$
13.6	$52.2^{+5.6\%}_{-7.4\%}$	$4.1^{+2.1\%}_{-1.5\%}$	$1.46^{+1.8\%}_{-1.9\%}$	$0.95^{+4.0\%}_{-3.6\%}$	$0.57^{+6.9\%}_{-9.9\%}$	$59.2^{+5\%}_{-7\%}$
14	$54.7^{+5.6\%}_{-7.4\%}$	$4.28^{+2.1\%}_{-1.5\%}$	$1.51^{+1.8\%}_{-1.9\%}$	$0.99^{+4.1\%}_{-3.7\%}$	$0.61^{+6.9\%}_{-9.8\%}$	$62.1^{+5\%}_{-7\%}$

2.2.2 SM Higgs boson branching ratios and total width

To thoroughly understand and interpret experimental data, it is vital to compute the decay widths of all relevant Higgs boson channels, along with a precise

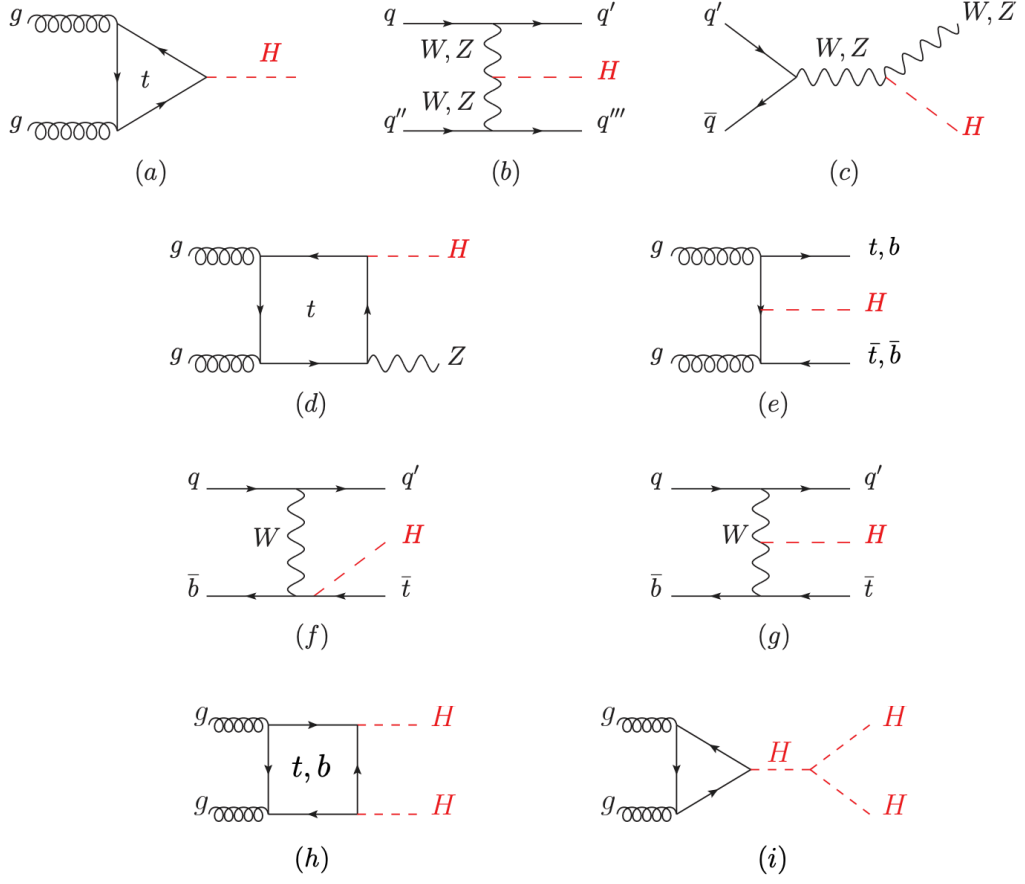


Fig. 2.4: The primary leading-order Feynman diagrams contributing to single Higgs boson production are: (a) gluon fusion, (b) vector-boson fusion, (c) Higgsstrahlung (or production associated with a gauge boson via a quark-quark interaction at tree level), (d) production associated with a gauge boson (at loop level via a gluon-gluon interaction), (e) production associated with a pair of top or bottom quarks, (f-g) production with a single top quark, and di-Higgs production through (h) top- and bottom-quark loops, and (i) Higgs boson self-coupling.

estimation of their associated uncertainties. This process also involves considering the potential decays of the Higgs boson into off-shell particles that subsequently decay into lighter Standard Model (SM) particles. A Higgs boson with a mass of approximately 125 GeV provides the opportunity to probe its interactions with various SM particles. The primary decay modes include $H \rightarrow b\bar{b}$ and $H \rightarrow WW^*$, followed by $H \rightarrow gg$, $H \rightarrow \tau^+\tau^-$, $H \rightarrow c\bar{c}$, and $H \rightarrow ZZ^*$. Decays with lower branching ratios, such as $H \rightarrow \gamma\gamma$, $H \rightarrow Z\gamma$, and $H \rightarrow \mu^+\mu^-$, though less frequent, are particularly insightful as they are loop-induced and provide indirect information on the Higgs couplings to WW , ZZ , and top quarks in various configurations.

The uncertainties in these branching ratios stem from the exclusion of higher-

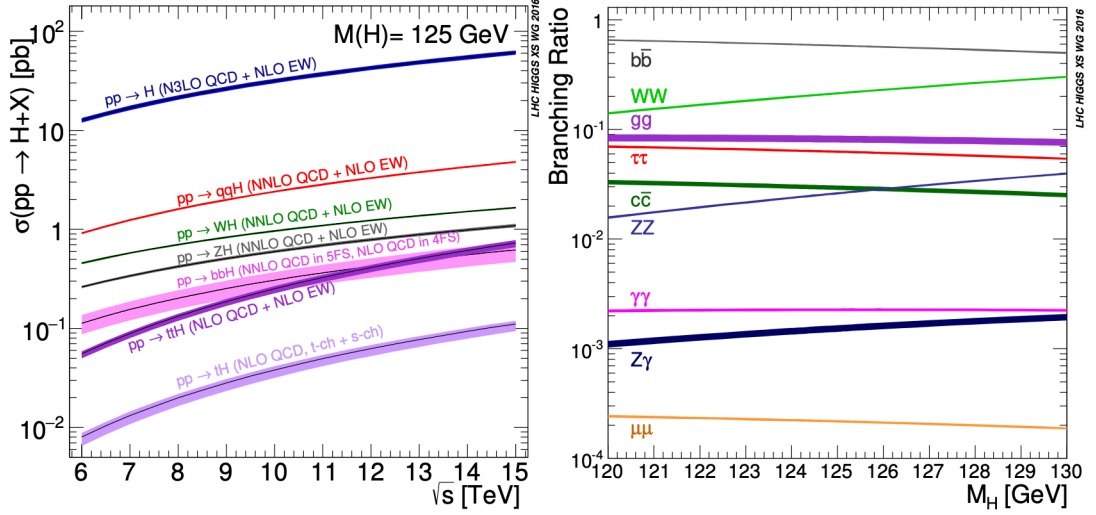


Fig. 2.5: (Left) The production cross sections of the SM Higgs boson as a function of the center-of-mass energy, $\sqrt{s}$, for pp collisions [4], with the VBF process labeled as qqH. (Right) The branching ratios for the primary decay modes of the SM Higgs boson around $m_H = 125$ GeV [5, 6], where theoretical uncertainties are represented by shaded bands.

order corrections in theoretical models and inaccuracies in the SM input parameters, particularly fermion masses and the QCD gauge coupling. These issues are comprehensively analyzed by the LHC Higgs Working Group, and detailed discussions can be found in the relevant literature [4]. The state-of-the-art theoretical calculations compiled by this group are crucial for accurate predictions, and further details are available in Refs. [29, 30, 5, 6, 77].

The computed total width of a 125 GeV Standard Model Higgs boson is $\Gamma_H = 4.07 \times 10^{-3}$ GeV, with an associated relative uncertainty of +4.0% to −3.9%. The branching ratios for the most significant decay channels of the SM Higgs boson, as a function of its mass m_H , including the latest theoretical uncertainties, are illustrated in Figure 2.5 (right) and summarized for $m_H = 125$ GeV in Table 11.3. For a more in-depth discussion of these calculations, readers are referred to the reviews provided in Refs. [29, 30, 5, 6].

2.3 Vector Boson Scattering

2.3.1 Definition of vector boson scattering

From the standpoint of experimental physics, a scattering process at the LHC is characterized by its observable final state, including particle jets, leptons, photons, or missing energy from neutrinos, which collectively define the event sig-

Table. 2.2: The branching ratios and corresponding relative uncertainties for a Standard Model Higgs boson with a mass of $m_H = 125$ GeV [5, 6]

Decay channel	Branching ratio	Rel. uncertainty
$H \rightarrow \gamma\gamma$	2.27×10^{-3}	2.1%
$H \rightarrow ZZ$	2.62×10^{-2}	$\pm 1.5\%$
$H \rightarrow W^+W^-$	2.14×10^{-1}	$\pm 1.5\%$
$H \rightarrow \tau^+\tau^-$	6.27×10^{-2}	$\pm 1.6\%$
$H \rightarrow b\bar{b}$	5.82×10^{-1}	$+1.2\%, -1.3\%$
$H \rightarrow c\bar{c}$	2.89×10^{-2}	$+5.5\%, -2.0\%$
$H \rightarrow Z\gamma$	1.53×10^{-3}	$\pm 5.8\%$
$H \rightarrow \mu^+\mu^-$	2.18×10^{-4}	$\pm 1.7\%$

nature. In contrast, the theoretical perspective defines a scattering process by its external particles and their interactions via strong and electroweak couplings within the framework of perturbative theory. While these experimental and theoretical definitions overlap, they also introduce potential ambiguities when aligning experimental data with theoretical predictions.

The study of Vector Boson Scattering (VBS) at the LHC is a prime example. VBS typically involves two gauge bosons emitted from separate quark lines, as depicted in the upper part of Figure 2.6. When dealing with heavy vector bosons (excluding photons), VBS is treated at the Born level with contributions of the order $\mathcal{O}(\alpha^6)$, including the decay products of these heavy bosons. The process typically features quarks in the initial state, producing final states with up to four leptons. This gives rise to three VBS signature categories at the LHC: fully leptonic ($2jets + 4leptons$), semi-leptonic/semi-hadronic ($4jets + 2leptons$), and fully hadronic (6 jets). This classification ensures gauge invariance and accommodates non-resonant, off-shell, and interference effects, as well as diagrams beyond the VBS, such as tri-boson contributions. To isolate VBS-specific diagrams, approximations such as the effective vector-boson framework [78, 79, 80, 81, 82] or vector-boson scattering techniques [83, 8] are employed.

2.3.2 Distinguishing VBS from Non-VBS Processes

Distinguishing VBS events from non-VBS processes, such as tri-boson production, is experimentally challenging due to the quantum-mechanical nature of these events. To mitigate non-VBS contributions, specific kinematic cuts—such as invariant mass cuts around the W/Z boson masses—or Monte Carlo subtraction techniques are often employed. The primary challenge lies in maintaining a VBS-enriched signal region, particularly when higher-order (NLO) contributions are present.

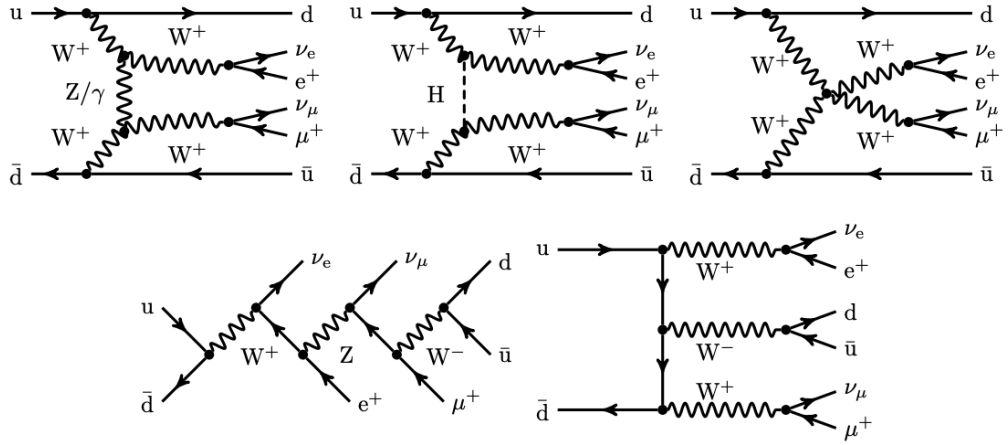


Fig. 2.6: Typical Feynman diagrams illustrating VBS contributions (top) and non-VBS contributions (bottom) to the process $pp \rightarrow \mu^+ \nu_\mu e^+ \nu_e jj$ are shown [7].

Apart from pure electroweak (EW) contributions at $\mathcal{O}(\alpha^6)$, VBS signatures include irreducible components from $\mathcal{O}(\alpha_s \alpha^5)$ and $\mathcal{O}(\alpha_s^2 \alpha^4)$. These components are typically categorized as EW (or VBS) signals, interference, and QCD backgrounds. On an event-by-event basis, it is challenging to unambiguously assign an event to any single contribution. However, experimental collaborations have successfully measured VBS processes in signal-enhanced phase space regions using specific kinematic cuts.

This approach is justified by the distinct behaviors of EW and QCD contributions, which peak in different regions of phase space due to their differing structures. The EW component lacks QCD exchanges between the quark lines, in contrast to the QCD component where such exchanges are common.

As a result, the differential cross section, as a function of the invariant mass or rapidity separation of the scattered quarks (the tagging jets), diverges significantly between these components. Typically, the EW contribution is characterized by tagging jets with large invariant masses (m_{jj}) and significant rapidity gaps (Δy_{jj}), effectively isolating the central event region from QCD-induced activity, particularly in fully leptonic signatures. The QCD contribution, conversely, shows the opposite behavior.

This contrast is clearly illustrated in Figure 2.7, which depicts two-dimensional differential distributions of the three contributions as functions of the invariant mass and rapidity separation of the tagging jets. Consequently, as with non-VBS contributions, appropriate cuts on the tagging jets' invariant mass and rapidity gap are essential for minimizing interference and/or QCD background, making these variables key discriminators in VBS measurements at the LHC.

QCD and interference components can also be subtracted using Monte Carlo

predictions to isolate VBS contributions. While effective at higher orders, this method is less meaningful at leading order (LO) due to the overlap of contributions. NLO contributions, involving multiple Born processes with associated amplitude corrections, further complicate the separation of EW and QCD signals.

Accurate VBS measurement, with minimal theoretical assumptions, demands the careful design of fiducial measurements robust against non-VBS backgrounds. This approach facilitates transparent comparisons between theory and experiment, enhancing our understanding of VBS dynamics. Recent studies have demonstrated the effectiveness of fiducial cross sections in separately analyzing EW and QCD components and their interplay [84, 85]. By focusing on multiple fiducial regions in experimental analyses, researchers can disentangle various physical effects, highlighting the unique characteristics of high-energy vector-boson scattering at the LHC.

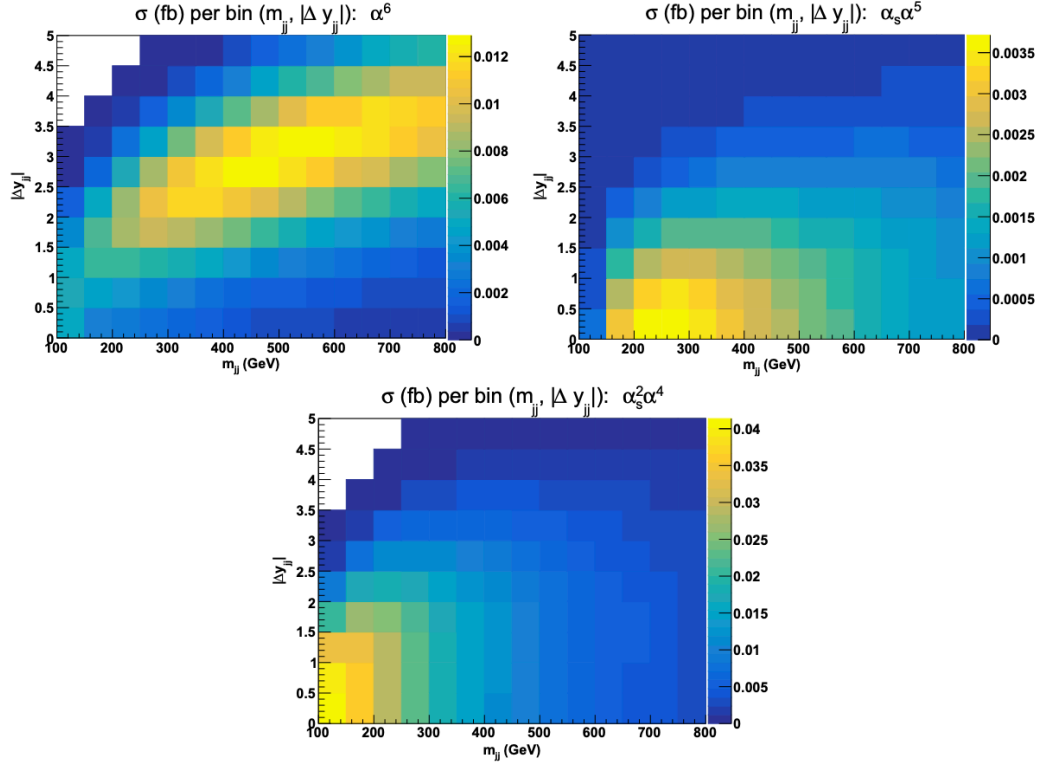


Fig. 2.7: Double-differential distributions are shown for the variables m_{jj} and $|\Delta y_{jj}|$, corresponding to the three leading-order contributions: $\mathcal{O}(\alpha^6)$ (top left), $\mathcal{O}(\alpha_s \alpha^5)$ (top right), and $\mathcal{O}(\alpha_s^2 \alpha^4)$ (bottom) [8]. Standard event selection criteria are applied, excluding cuts on m_{jj} and $|\Delta y_{jj}|$.

2.3.3 Handling QCD and Interference Contributions in VBS Measurements

One approach to managing QCD and interference contributions in VBS studies is to subtract them using Monte Carlo simulations. This aims to isolate VBS

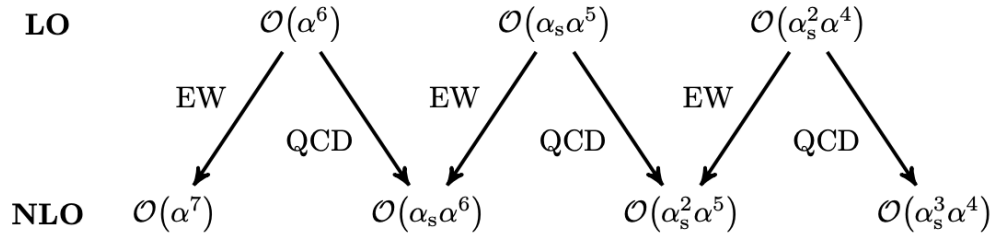


Fig. 2.8: All contributing orders for VBS processes at the LHC are presented at both LO and NLO levels [7].

signals from their irreducible backgrounds. While this method may be somewhat effective at leading order (LO), it becomes less relevant at next-to-leading order (NLO) and beyond. At LO, including interference effects with either the electroweak (EW) signal or the QCD background is arbitrary, as these effects inherently mix characteristics of both.

At the NLO level, the complexity increases, as shown in Figure 2.8. There are up to four distinct Born amplitudes involved, with some being of mixed type. This means that corrections apply to two different underlying processes. Because these corrections are linked by infrared singularities, they cannot be cleanly separated into purely EW or purely QCD contributions without additional assumptions. Therefore, defining an NLO signal or background inevitably relies on theoretical approximations.

To reduce dependence on theoretical assumptions and allow for clearer comparison between theory and experiment, fiducial measurements should avoid subtracting any contributions—whether from QCD, interference, or tri-boson backgrounds. Instead, these contributions can be highlighted separately after the fact, allowing for more accurate analysis. This approach helps capture the essential features of VBS physics and supports better comparison between experimental data and theoretical predictions. Recent work, such as in Refs. [84, 85], illustrates the value of presenting fiducial cross sections for both EW and QCD components, analyzed individually and together.

Moreover, using multiple fiducial regions in experiments allows for the study of different physical effects. Looser cuts often result in dominance by QCD backgrounds or tri-boson contributions. Tighter, VBS-specific cuts better isolate the characteristics of high-energy vector boson scattering. These varied approaches reveal the multifaceted nature of VBS processes, which are crucial to explore in high-energy physics.

2.3.4 Higgs mass and couplings in vector boson scattering

The high-energy behavior of vector boson scattering (VBS), particularly in processes such as $W_L^+ W_L^+ \rightarrow W_L^+ W_L^+$, is a crucial test for the Standard Model (SM) Higgs mechanism. The SM predicts that the Higgs boson, through its coupling to vector bosons (HWW), cancels the quadratic divergences that arise in the scattering amplitudes, ensuring unitarity at high energies. This precise cancellation is a fundamental feature of the SM and is a key aspect in confirming the validity of the Higgs boson discovered at the LHC. Any deviation from this cancellation could indicate new physics, particularly if unitarity were violated at high enough energies—a scenario that the SM predicts should not occur.

At the heart of this analysis is the behavior of the total and differential cross sections for the scattering of longitudinally polarized W and Z bosons at energies much higher than their masses. These cross sections are experimentally accessible and serve as a testing ground for the SM. The longitudinal polarization ($W_L^+ W_L^+$) is particularly sensitive to the details of electroweak symmetry breaking, making it a critical probe of the Higgs sector.

A tree-level analysis of $W_L^+ W_L^+$ scattering reveals that the total cross section's dependence on the center of mass energy is strongly influenced by the Higgs mass and the HWW coupling strength. In the SM scenario, where the HWW coupling is as predicted, the amplitude grows with energy until it reaches the Higgs mass threshold, after which it flattens. This plateauing behavior is crucial for maintaining unitarity. In the absence of the Higgs boson, however, the amplitude would continue to rise, potentially leading to unitarity violation at an energy scale around 1.2 TeV. Such a violation would imply the presence of new physics beyond the SM, as the scattering amplitude would need to be moderated before reaching this critical energy.

When the HWW coupling deviates from the SM prediction, the scattering cross section exhibits a different pattern, either decreasing or increasing depending on whether the coupling is weaker or stronger than the SM value. This behavior is a direct consequence of incomplete cancellation of the quadratic divergences, and it becomes particularly noticeable at high energies where the quadratic term dominates. The cross sections for g_{HWW} and $1 - g_{HWW}$ eventually converge as energy increases, underscoring the importance of precise measurements in this regime.

Moreover, the angular distribution of the scattered W_L^+ bosons provides additional insight into the Higgs boson's properties. In the SM with a light Higgs, scattering predominantly occurs at small angles, but at higher energies, deviations manifest as a secondary peak at large angles, indicating possible new physics. This

angular dependence is expected not only in $W_L^+ W_L^+$ scattering but also in other processes like $W^- W^-$ and ZZ pairs, making these channels equally important for probing the Higgs mechanism.

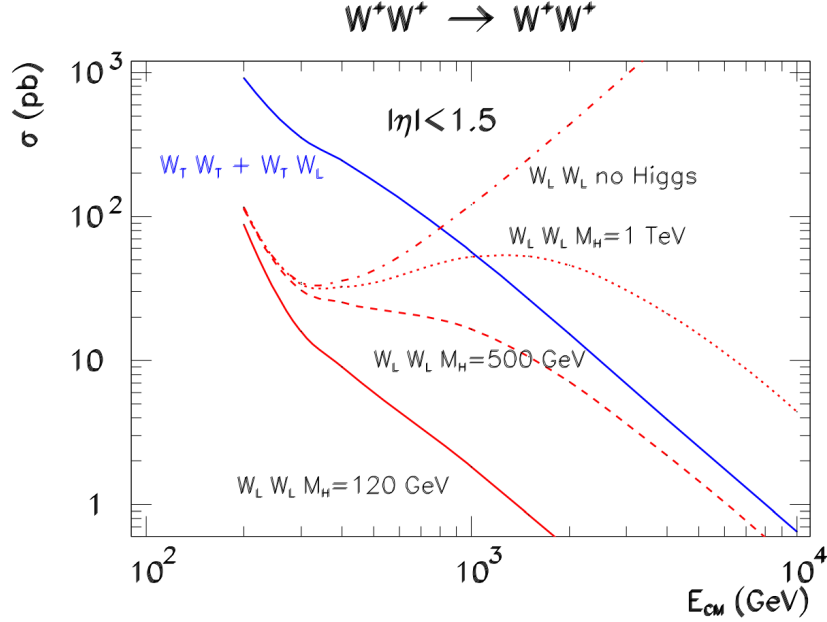


Fig. 2.9: The total cross sections for W^+W^+ scattering are shown as a function of center-of-mass energy for various initial and final state polarizations, as well as different Higgs boson masses, including the Higgsless limit. Two on-shell, unpolarized W^+ beams are assumed in the analysis. A pseudorapidity cut of ± 1.5 with respect to the incoming W direction is applied. The $W_T W_T + W_T W_L$ curves for each Higgs mass coincide within the width of the blue line. The results are based on calculations using MadGraph [9, 10, 11].

Figure 2.9 illustrates the total $W_L^+ W_L^+$ scattering cross sections as a function of center of mass energy for different initial and final state polarizations and Higgs masses, including scenarios without a Higgs boson. The plot highlights the energy-dependent behavior of the scattering process, with distinct features corresponding to different HWW couplings. These variations provide crucial data for testing the SM and exploring potential deviations that could signal new physics.

2.3.5 The $W\gamma jj$ final states

Although not directly linked to the Electroweak Symmetry Breaking (EWSB) mechanism, the study of vector boson scattering (VBS) processes resulting in final states like $W^\pm \gamma jj$ provides valuable insights for validating Standard Model (SM) predictions as well as probing BSM physics. These processes exhibit significant theoretical and experimental parallels with the scattering of heavy gauge bosons. The clean identification of high-energy photons, unaccompanied by secondary par-

ticle decays, significantly enhances the fiducial cross section measurements. In both scenarios, the analysis is confined to leptonic decays of the W boson. Given this constraint, $W\gamma jj$ production primarily arises from QCD-induced diagrams, which constitute the main background. In addition, there remain non-negligible contributions from Standard Model processes involving top quarks and photon emissions.

2.4 Physics beyond the Standard Model

2.4.1 Introduction to New Physics Beyond the Standard Model

The pursuit of physics beyond the Standard Model (BSM) is motivated by the Standard Model's limitations in addressing fundamental unresolved questions in contemporary physics. Despite its remarkable success in describing a wide range of phenomena, the SM does not incorporate the effects of gravity, as described by general relativity, and fails to account for the nature of dark matter and dark energy, which together constitute approximately 95% of the universe's total energy density. Moreover, the observed asymmetry between matter and antimatter remains unexplained within the SM framework, challenging our understanding of baryogenesis and the initial conditions of the universe. Furthermore, the hierarchy problem raises concerns about the stability of the Higgs boson mass under quantum corrections, suggesting that new physics may emerge at energy scales accessible by current or future colliders.

Theoretical frameworks such as supersymmetry, which proposes a symmetry between fermions and bosons, offer potential solutions to these issues by predicting the existence of partner particles that could stabilize the Higgs mass and provide a candidate for dark matter. Similarly, models incorporating extra dimensions, such as those inspired by string theory, suggest that additional spatial dimensions could reveal new gravitational phenomena at higher energy scales. Composite Higgs models propose that the Higgs boson is not an elementary particle but rather a composite state, which could provide insights into the fundamental structure of matter. Each of these BSM scenarios suggests the existence of new particles and interactions, compelling physicists to conduct extensive searches at high-energy colliders, such as the LHC, to uncover signatures of new physics that challenge the current paradigm.

Among the most pressing inquiries in BSM physics is the investigation of the Higgs boson self-coupling, which is pivotal for understanding electroweak symmetry breaking and the stability of the electroweak vacuum. The search for di-Higgs production (HH) at colliders is integral to probing this self-interaction, providing

a means to measure the quartic coupling associated with the Higgs field. Such measurements not only test the consistency of the SM but also have the potential to uncover signatures of BSM physics if deviations from SM predictions are observed. Additionally, the decay channel $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ serves as a promising approach to investigate new scalar particles S that may arise in various BSM scenarios. Detecting this decay mode offers critical insights into the nature of the scalar S and its coupling to the Higgs boson H , thereby elucidating the underlying dynamics of the extended Higgs sector and its implications for future theoretical developments in high-energy physics.

2.4.2 Di-Higgs Production: Probing Higgs Self-Interaction and BSM Physics

The search for di-Higgs (HH) production is crucial for deepening our understanding of the fundamental properties of the Higgs boson and the mechanism of electroweak symmetry breaking. While the SM has been extensively validated, the shape of the Higgs potential—particularly its self-interaction—remains one of the least understood aspects of particle physics. Di-Higgs production is directly sensitive to this self-coupling, which governs the form of the Higgs potential. It is predicted to have an exceedingly low cross section of approximately 33.5 fb at a center-of-mass energy of 14 TeV at the LHC [86, 87]. The rarity of this process within the SM poses significant challenges for its detection, yet its measurement is immensely valuable.

Constraining the rate of di-Higgs production would provide a direct measurement of the Higgs self-coupling. Any deviation from the SM predictions could suggest the presence of new BSM physics. Numerous BSM theories, including those proposing new scalar fields or modifications to the Higgs potential, predict enhanced rates of di-Higgs production or alterations in the kinematic distributions of the final states. These modifications could indicate new particles or forces that influence the dynamics of the Higgs sector.

The significance of di-Higgs searches extends beyond simply validating the Standard Model. These searches provide critical insights into the stability of the Higgs potential. The stability of the Higgs potential is closely tied to the mechanisms of electroweak symmetry breaking and has important implications for the fate of the universe, especially within high-energy physics and early-universe cosmology. Determining whether the Higgs vacuum is stable, metastable, or unstable is a central question that di-Higgs production studies aim to clarify.

Given its critical importance, di-Higgs production is a central focus of the LHC’s physics program and will continue to be a priority for future collider experiments. Ongoing and forthcoming analyses are essential for either observing

this rare process or placing stringent limits on the Higgs self-coupling and potential BSM effects. Achieving a comprehensive understanding of the Higgs sector is vital for completing the SM and could pave the way for new physics that extends beyond the current theoretical framework. Thus, di-Higgs searches serve not only as a crucial test of the SM but also as a gateway to uncovering unknown aspects of fundamental physics.

2.4.3 The Role of $X \rightarrow SH$ in BSM Physics

The $X \rightarrow SH$ process serves as a pivotal pathway in the exploration of BSM physics. In this process, where X denotes a heavier scalar or pseudoscalar particle and S represents a lighter scalar, additional contributions are introduced that may act either as a background or, under certain model-dependent circumstances, overshadow the di-Higgs signal. Consequently, the analysis of $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ emerges as a critical component in a comprehensive exploration of BSM physics.

The manifestation of the $X \rightarrow SH$ transition implies a more intricate Higgs sector than what is encapsulated within the minimal Standard Model framework. Such complexity naturally arises in models that extend the SM Higgs sector through the introduction of additional scalar fields, either as singlets or doublets.. These extended models offer profound insights into a range of phenomena, including but not limited to electroweak symmetry breaking, CP violation, and dark matter interactions [88].

Furthermore, the decay channels $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ present significant experimental advantages. The $S \rightarrow b\bar{b}$ decay is particularly favored due to its relatively large branching ratio, which enhances the detectability of such events. Conversely, the $H \rightarrow \gamma\gamma$ decay, while less frequent, provides a remarkably clean signal with minimal background interference. This complementary nature of the $b\bar{b}\gamma\gamma$ final state thus establishes it as an optimal probe for BSM physics, capable of revealing potential deviations in Higgs couplings and self-interactions. Such deviations would constitute strong evidence for BSM phenomena, offering crucial insights into the structure of new physics.

Across all the discussed theoretical models, the $SU(2)_L$ gauge structure of the Standard Model remains preserved, ensuring compatibility with existing electroweak precision measurements. However, the introduction of additional scalar fields inevitably modifies the dynamics of electroweak symmetry breaking, leading to the emergence of new mass eigenstates. The phenomenology of $X \rightarrow SH$ processes, along with their experimental signatures, is dictated by the interplay among these new states, which is in turn governed by the mixing angles and coupling strengths specific to each model.

2.4.4 Extended Higgs Sector Models for $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$

Several theoretical BSM models that can accommodate the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ process are introduced. Each model offers unique insights and potential solutions to existing problems in particle physics, such as electroweak baryogenesis, dark matter, and the hierarchy problem.

2.4.4.1 Complex Singlet Extension of the SM

The Complex Singlet Extension [50] introduces a complex scalar field S that is a singlet under the $SU(2)_L$ gauge group. This extension is motivated by the need to address limitations inherent in the minimal Higgs sector, particularly in scenarios involving electroweak baryogenesis and the generation of dark matter. The additional scalar field S is integrated into the SM Higgs potential, resulting in an extended scalar sector with modified mass spectra and interaction vertices. The scalar potential governing this model is expressed as:

$$V(H, S) = -\mu^2 H^\dagger H + \lambda(H^\dagger H)^2 + \mu_S^2 |S|^2 + \lambda_S |S|^4 + \lambda_{HS} |H|^2 |S|^2. \quad (2.12)$$

The interaction term λ_{HS} facilitates the mixing between the SM Higgs doublet H and the singlet S , leading to the formation of mass eigenstates that could be observed experimentally through processes such as $X \rightarrow SH$. This model is particularly appealing for addressing open questions in cosmology and particle physics, such as the nature of dark matter and the source of additional CP violation required for baryogenesis [50]. Moreover, the decay channels $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ provide both a large branching ratio and a clean signal, respectively, making them ideal for experimental searches.

2.4.4.2 Two-Real-Scalar-Singlet Extension

To appreciate the complexity and motivation behind the “Two-Real-Scalar-Singlet Extension”, it is essential to first discuss the foundational “Two-Real-Scalar Model (TRSM)” [89]. The TRSM extends the SM by introducing two additional real scalar fields, S_1 and S_2 , that interact with the SM Higgs doublet. This model was developed to explore the rich phenomenological implications of an extended scalar sector without significantly altering the predictions of the SM. The scalar potential for the TRSM is described by:

$$V(H, S_1, S_2) = -\mu^2 H^\dagger H + \lambda(H^\dagger H)^2 + \frac{1}{2}\mu_1^2 S_1^2 + \frac{1}{2}\mu_2^2 S_2^2 + \lambda_{HS_1} H^\dagger H S_1^2 + \lambda_{HS_2} H^\dagger H S_2^2 + \lambda_{S_1 S_2} S_1^2 S_2^2. \quad (2.13)$$

Building on the TRSM, the “Two-Real-Scalar-Singlet Extension” incorporates mixing between the SM Higgs doublet and the two singlet fields, S_1 and S_2 , resulting in a more intricate scalar potential. This model allows for diverse phenomenological outcomes, including the possibility of $X \rightarrow S_1 H$ or $X \rightarrow S_2 H$, each leading to different final states. The scalar potential for this extended model is formulated as:

$$\begin{aligned}
V(H, S_1, S_2) = & -\mu^2 H^\dagger H + \lambda(H^\dagger H)^2 + \frac{1}{2}\mu_1^2 S_1^2 + \frac{1}{2}\mu_2^2 S_2^2 \\
& + \lambda_{HS_1} H^\dagger H S_1^2 + \lambda_{HS_2} H^\dagger H S_2^2 + \lambda_{S_1 S_2} S_1^2 S_2^2 + \mu_{S_1 S_2} S_1 S_2 + \lambda_3 S_1^3 + \lambda_4 S_2^3.
\end{aligned}
\tag{2.14}$$

This extended model is particularly significant for exploring cosmological phenomena, such as the relic density of dark matter and the conditions required for a strong first-order electroweak phase transition, which is necessary for baryogenesis [89]. The decay channels $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ remain highly effective due to their favorable branching ratios and clean experimental signatures, making them prime targets for collider-based searches.

2.4.4.3 Complex Two-Higgs-Doublet Model (2HDM)

The Complex Two-Higgs-Doublet Model (2HDM) [88] expands the SM by introducing a second Higgs doublet, resulting in a more intricate Higgs sector with five physical Higgs bosons. This model addresses several critical issues in the SM, including the hierarchy problem, and provides a natural framework for CP violation beyond the SM, which is essential for explaining the matter-antimatter asymmetry in the universe. The scalar potential for the 2HDM, which allows for CP-violating terms, is given by:

$$\begin{aligned}
V(\Phi_1, \Phi_2) = & m_{11}^2 |\Phi_1|^2 + m_{22}^2 |\Phi_2|^2 - (m_{12}^2 \Phi_1^\dagger \Phi_2 + \text{h.c.}) \\
& + \frac{\lambda_1}{2} |\Phi_1|^4 + \frac{\lambda_2}{2} |\Phi_2|^4 + \lambda_3 |\Phi_1|^2 |\Phi_2|^2 \\
& + \lambda_4 |\Phi_1^\dagger \Phi_2|^2 + \frac{\lambda_5}{2} [(\Phi_1^\dagger \Phi_2)^2 + \text{h.c.}].
\end{aligned}
\tag{2.15}$$

In the context of BSM physics, the 2HDM provides multiple avenues for new phenomena. For instance, the heavier scalar X could be a pseudoscalar A or a heavy scalar H , while the lighter scalar S could be the CP-even scalar H . This setup allows for a diverse range of processes, including $X \rightarrow SH$, making the 2HDM a compelling candidate for BSM investigations [88]. As in other models, the $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ decay channels are particularly advantageous due to

their clean experimental signatures and significant branching ratios.

2.4.4.4 2HDM Extended by a Real Scalar Singlet

The 2HDM extended by a real scalar singlet further refines the 2HDM by introducing an additional scalar singlet field S that interacts with both Higgs doublets. This model is motivated by the desire to combine the advantages of the 2HDM with the potential benefits of an additional scalar degree of freedom, such as addressing the dark matter problem or enhancing the strength of the electroweak phase transition. The scalar potential for this extended model is expressed as:

$$V(\Phi_1, \Phi_2, S) = V(\Phi_1, \Phi_2) + \frac{1}{2}\mu_S^2 S^2 + \lambda_{HS} S^2(|\Phi_1|^2 + |\Phi_2|^2) + \lambda_S S^4. \quad (2.16)$$

This extended model leads to a richer Higgs phenomenology, including the possibility of new resonant channels such as $X \rightarrow SH$. The decay channels $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$, as discussed in previous models, remain experimentally favorable due to their combination of a large branching ratio and a clean signal [90].

2.4.4.5 Next-to-Minimal Supersymmetric Standard Model (NMSSM)

Before delving into the Next-to-Minimal Supersymmetric Standard Model (NMSSM) [91], it is crucial to introduce its predecessor, the Minimal Supersymmetric Standard Model (MSSM). The MSSM extends the SM by introducing supersymmetric partners for all SM particles, thus providing a solution to several theoretical challenges, including the hierarchy problem. However, the MSSM encounters the so-called μ -problem, which arises from the need to introduce a supersymmetric mass term for the Higgs fields, without any natural explanation for its scale.

The NMSSM was developed to resolve the μ -problem by introducing a singlet superfield S that couples to the Higgs doublets H_u and H_d , thereby dynamically generating the μ term. The superpotential of the NMSSM is given by:

$$W_{\text{NMSSM}} = W_{\text{MSSM}} + \lambda \hat{S} \hat{H}_u \cdot \hat{H}_d + \frac{\kappa}{3} \hat{S}^3, \quad (2.17)$$

where $\hat{S}$ is the singlet superfield. The NMSSM predicts an extended Higgs sector comprising seven Higgs bosons, thereby providing multiple potential channels for the $X \rightarrow SH$ process. The interplay between supersymmetry and the extended Higgs sector in the NMSSM offers a comprehensive framework for exploring deviations from the SM, particularly in the $b\bar{b}\gamma\gamma$ final state [91]. The $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ decay modes are particularly effective, combining high branching ratios with clean experimental signals.

2.4.5 Conclusion

The study of the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ process within various extended Higgs frameworks has highlighted the potential for discovering BSM physics. Each of the theoretical models discussed—ranging from the complex singlet extension, two-real-scalar-singlet extension, NSSM, NMSSM, to the 2HDM variants—offers unique insights into unresolved questions in particle physics. These models address issues such as CP violation, dark matter, and the nature of the electroweak phase transition, all while providing testable predictions for new scalar particles.

The models explored in this paper introduce additional scalar fields, which can mix with the Standard Model Higgs boson, leading to rich phenomenology involving new resonances and altered decay channels. Particularly, the $X \rightarrow SH$ process serves as a significant probe for these new physics scenarios, with the $S \rightarrow b\bar{b}$ and $H \rightarrow \gamma\gamma$ decay channels offering a combination of a large branching ratio and a clean experimental signature, making them highly suitable for collider searches.

Leveraging the ATLAS Run-2 data, the search for two additional scalar bosons X and S , where $m_X > m_S + m_H$ —becomes a crucial aspect of testing these BSM models. This analysis not only seeks to confirm the existence of these new particles but also aims to deepen our understanding of the extended Higgs sector and its implications for broader BSM physics.

Future experiments and data analyses will be pivotal in either confirming or challenging the predictions made by these models, potentially leading to significant discoveries in the field of particle physics. The continued exploration of the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ process stands as a promising avenue for uncovering the next layer of fundamental physics beyond the Standard Model.

CHAPTER 3

Large Hadron Collider and the ATLAS Detector

The experiments conducted at the Large Hadron Collider (LHC) at CERN mark our deepest venture into the energy frontier of particle physics. The objective of investigating physical phenomena at the TeV scale imposes stringent demands on both the accelerator's and the detectors' performance, which in turn dictate the impressive scale of both the machinery and the experimental setup.

3.1 Large Hadron Collider

The Large Hadron Collider (LHC) stands as a testament to the advancements in particle acceleration technology, marking the most notable enhancement to the European Organization for Nuclear Research (CERN)'s accelerator complex since its inauguration on the 10th of September, 2008. With a circumference of 27 kilometers, the LHC comprises a ring equipped with superconducting magnets, augmented by a series of accelerating structures designed to increase the kinetic energy of particles during the acceleration phase. The facility accelerates two high-energy particle beams to velocities approaching the speed of light, circulating in opposite directions within separate ultra-high vacuum tubes until they are made to collide.

The orientation and acceleration of these beams are governed by a potent magnetic field produced by superconducting electromagnets. These electromagnets are made from coils of a unique electrical cable that achieves superconductivity when cooled to -271.3°C , facilitating electricity conduction without resistance or energy dissipation. This extremely low temperature is maintained via a distribution system for liquid helium, which cools the magnets and ensures the LHC's operational efficacy.

A diverse array of thousands of magnets, differing in type and size, is employed to steer the particle beams around the LHC's periphery. This assembly comprises 1232 dipole magnets, each 15 meters in length, which arc the beams, and 392 quadrupole magnets, with lengths between 5 to 7 meters, which focus the beams.

The CERN accelerator complex *Complexe des accélérateurs du CERN*

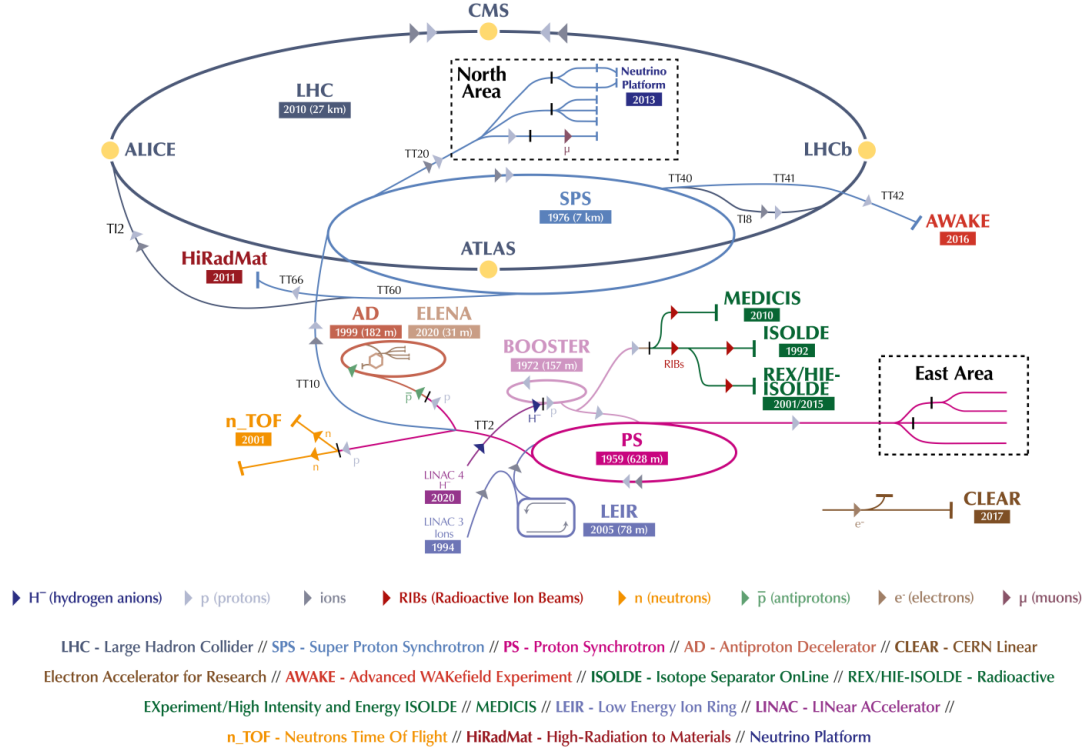


Fig. 3.1: The LHC represents the final stage (depicted by the dark blue line) in a complex sequence of particle accelerators. Smaller accelerators are utilized in this chain to gradually increase particle energy, delivering beams to a variety of smaller experiments, all of which seek to explore the fundamental mysteries of the universe.

To increase the probability of collisions, a specific group of magnets is utilized to compress the beams immediately before collision. The task of aligning these diminutive particles for collision is remarkably precise, equating to the challenge of intersecting two needles from a distance of 10 kilometers with exact accuracy.

The oversight of the LHC, including its supportive services and technical infrastructure, is centralized at the CERN Control Centre. This facility orchestrates the collision of particle beams at four specific locations along the accelerator's ring. These locations are aligned with the sites of four significant particle detectors: ATLAS, CMS, ALICE, and LHCb, each indispensable to the LHC's experimental pursuits.

3.2 ATLAS Detector

The ATLAS (A Toroidal LHC ApparatuS) detector is one of the four experiments which will measure p-p (and Pb ion) collisions at the Large Hadron

Collider (LHC). The LHC is a 26.7 km ring which will provide collisions at a nominal center-of-mass energy of 14 TeV for protons (1150 TeV for Pb ions) with a design luminosity of $10^{34} \text{cm}^{-2} \text{s}^{-1}$. Each LHC beam is composed of 2808 bunches, each containing 10^{11} protons and with a transverse size of $16 \mu\text{m}$ at the interaction points. The bunch crossing rate is 40 MHz (one crossing every 25ns), resulting in a pile-up of 20 events at peak luminosity. This is an important challenge for the hardware and data acquisition of the four LHC experiments. With this unprecedented energy, the LHC detectors will be used to probe for new physics beyond the Standard Model.

ATLAS is a multi-purpose particle physics detector, which means it should be able to measure the signatures of all the possible final states. We expect to observe from proton-proton (or heavy ion) collisions. They include main tracks from charged particles (hadrons, electrons, muons), energy deposition of electromagnetic and hadronic matter in the calorimeter system (through showering of the particles in many interaction length of material) and tracks from muons escaping the detector. The two main tracking devices, the Inner Detector and the Muon Spectrometer lie inside magnetic fields to allow the measurement of charge and momentum using the tracks. The passage of neutrinos through the detector can be measured using the missing transverse energy in the hermetically closed detector volume. A detailed description of the detector and its performance is presented here.

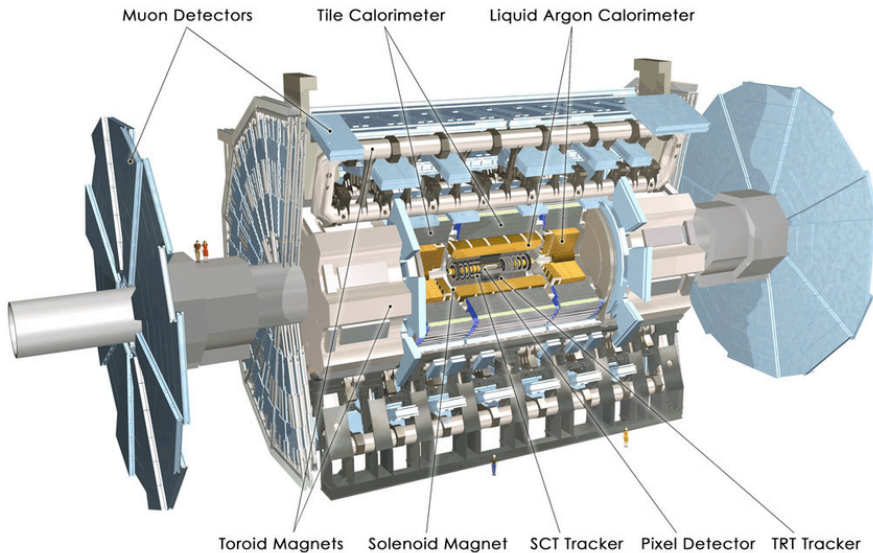


Fig. 3.2: Schematic diagram of the ATLAS detector system.

The overall ATLAS detector layout is shown in Figure 3.2 and its main performance goals are listed in Table 3.1. It is important to note that, for high- p_T muons, the muon-spectrometer performance as given in table 3.1 is independent

Table. 3.1: Overview of the primary performance objectives of the ATLAS detector. It should be noted that for high- p_T muons, the muon spectrometer operates independently of the inner detector system. Energy (E) and transverse momentum (p_T) are both expressed in GeV.

Detector component	Required resolution	η coverage	
		Measurement	Trigger
Tracking	$\sigma_{p_T}/p_T = 0.05\%p_T \oplus 1\%$	± 2.5	± 2.5
EM calorimetry	$\sigma_E/E = 10\%/\sqrt{E} \oplus 0.7\%$	± 3.2	± 2.5
Hadronic calorimetry (jets)	$\sigma_E/E = 50\%/\sqrt{E} \oplus 3\%$ $\sigma_E/E = 100\%/\sqrt{E} \oplus 10\%$	± 3.2	± 3.2
Muon spectrometer	$\sigma_{p_T}/p_T = 10\%$ at $p_T = 1$ TeV	± 2.7	± 2.4

of the inner-detector system.

The ATLAS detector is nominally forward-backward symmetric with respect to the interaction point. The magnet configuration comprises a thin superconducting solenoid surrounding the inner-detector cavity, and three large superconducting toroids (one barrel and two end-caps) arranged with an eight-fold azimuthal symmetry around the calorimeters. This fundamental choice has driven the design of the rest of the detector.

3.2.1 ATLAS Coordinate System

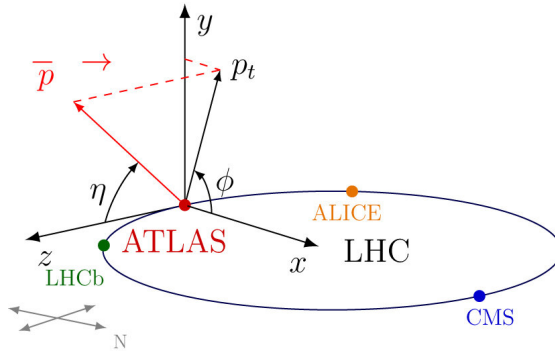


Fig. 3.3: Representation of the coordinate systems employed in the ATLAS experiment within the geographical framework of the LHC [12].

The ATLAS detector employs a right-handed coordinate system where the interaction point (IP) constitutes the origin. The x -axis is oriented towards the center of the Large Hadron Collider (LHC) ring, the y -axis is directed upwards, and the z -axis aligns with the beam direction. The detector's sides are designated as side-A and side-C, corresponding to the positive and negative z directions, respectively. The azimuthal (ϕ) and polar (θ) angles are defined relative to the beam axis. Furthermore, the pseudo-rapidity (η) is articulated as a function of

the polar angle θ , and the rapidity (Y) is defined through the energy (E) and the z -component of the momentum (p_Z). These definitions are crucial for addressing the behavior of massive particles within the detector framework.

3.2.2 Inner detector

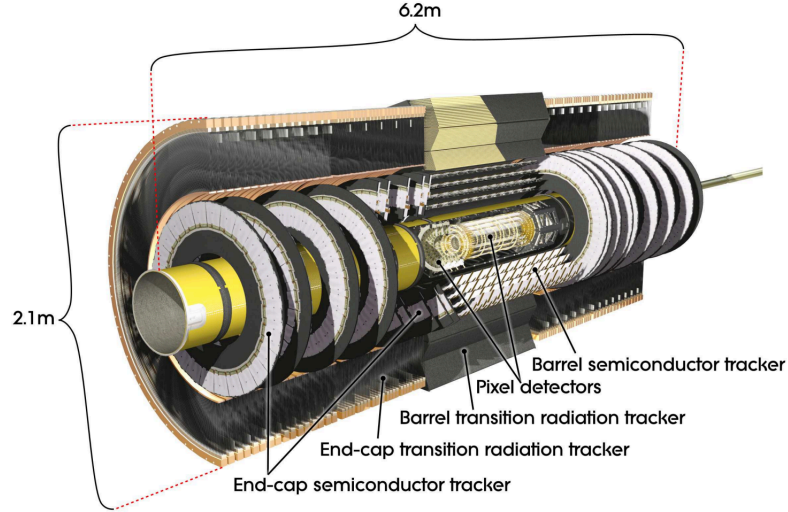


Fig. 3.4: Cut-away diagram of the ATLAS inner detector, displaying the barrel and end-cap sections of the pixel, SCT, and TRT detectors [13].

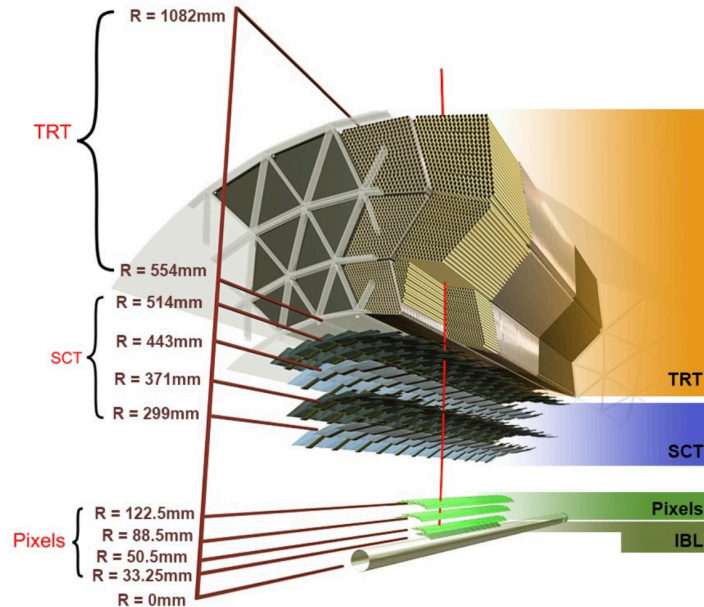


Fig. 3.5: Cross-sectional view of the barrel components of the ATLAS inner detector (ID) [13].

In the vicinity of the collision point, the emergence of approximately 1000

particles every 25 ns within the pseudo-rapidity range of $|\eta| < 2.5$ results in a significantly high track density within the detector. To fulfill the stringent requirements for momentum and vertex resolution stipulated by the benchmark physics processes, it is imperative to conduct high-precision measurements. This necessitates the deployment of detectors characterized by fine granularity. In this context, the integration of pixel detectors and silicon microstrip (SCT) trackers, in tandem with the straw tubes constituting the Transition Radiation Tracker (TRT), provides the requisite attributes for achieving the aforementioned objectives.

3.2.3 Calorimeters

The ATLAS calorimeters are located on the outside of the ID and are dedicated to measure the energy lost by the particles as they pass through the detector volume. The detectors consist of multiple layers of absorbing high-density material designed to deposit all the energy of the particles within the detector volume. The incoming particles will interact with the absorber material of the calorimeter, initiating a shower of secondary particles. Broadly speaking, there are two types of calorimeters: electromagnetic calorimeters dedicated to electromagnetic shower and hadronic calorimeters for hadronic shower. The electromagnetic calorimeter in the ATLAS detector has a η coverage that matches the ID and is ideally suited for precision measurements of electrons and photons with fine granularity. The hadronic calorimeter has readout cells with coarser granularity but is sufficient to satisfy the requirements for jet reconstruction and transverse momentum measurement. Figure 3.6 provides a view of the calorimeter systems, where the labeled systems are based on detector technology rather than physics purposes.

3.2.3.1 Electromagnetic calorimeter

Outside the ID and solenoidal magnet system is the high-granularity lead-liquid argon (LAr) sampling electromagnetic (EM) calorimeter for measuring the energy deposits from jets, photons and electrons and contributing to the measurement of missing transverse energy. The EM calorimeter is divided into a barrel and two end-cap sections, each housed in their own cryostat, to cover the entire range within $|\eta| < 3.2$. The cooled LAr fills the gaps between layers of accordion structure. Particles, such as photons and electrons, will interact with the lead absorbers as they pass through mainly via the bremsstrahlung, in which an electron radiates a photon, which can further produce an e^+e^- pair. This can instigate showering until the particles fall below a critical energy where ionisation begins to dominate rather than showering. The resulting electrons and photons ionise LAr, producing drift electrons in quantities proportional to its energy. These electrons are accelerated across the 2.1 mm drift gap with an operating voltage around 2kV

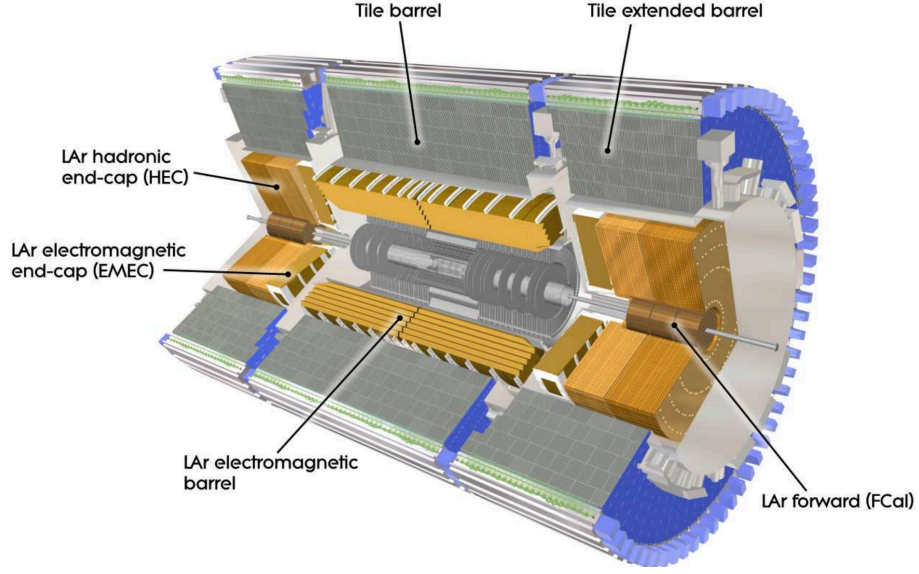


Fig. 3.6: Cross-sectional diagram of the ATLAS calorimeter system, showing the labeled liquid-argon and scintillating-tile subsystems [13].

provided by the copper electrodes that collect the resulting pulse and transmit it to the readout electronics.

To ensure that the majority of electrons and photons are completely contained within the EM calorimeter, the barrel section is designed with at least 22 radiation lengths (X_0) in thickness at all points, while the end-cap sections have a thickness of at least $24 X_0$ for $|\eta| > 1.475$ and $36 X_0$ at the high $|\eta|$ region.

In the region of $|\eta| < 1.8$, a presampler detector is used to correct for the energy lost by electrons and photons upstream of the calorimeter. The presampler consists of an active LAr layer with a thickness of 1.1 cm in the barrel region and 0.5 cm in the end-cap region [13].

3.2.3.2 Hadronic calorimeter

Strongly charged particles that are not completely contained within the EM calorimeter are stopped by the hadronic calorimeter placed directly outside the EM calorimeter envelope. The energy of those particles is lost through the formation of hadronic showers. The hadronic shower is a series of inelastic hadronic interactions of the primary particle with the nuclei of the absorber material. Secondary particles will undergo further inelastic interactions and produce more particles. The evolution of a hadronic shower is more complex than the EM shower because it involves producing EM showers and takes longer to develop, which requires the calorimeter a significant absorber thickness to fully contain the showers than the EM calorimeter. This is the reason that the hadronic calorimeter is placed

surrounding the EM calorimeter and not the other way around. The hadronic calorimeter system is composed of both scintillating tile and LAr components with 8 – 12 interaction lengths deep.

The central calorimeter region consists of the tile calorimeter composed of a barrel covers the region $|\eta| < 1.0$, and two extended barrels cover the range $0.8 < |\eta| < 1.7$. It is segmented radially into three layers with depths of approximately 1.5, 4.1 and 1.8 interaction lengths, and also extends from an inner radius of 2.28 m to an outer radius of 4.25 m. Since it has less harsh environment in terms of radiation dose, the scintillating tiles composed by 64 modules are situated in $(r-\phi)$ inside the steel absorber. Scintillation light uses wavelength-shifting fibers that are fed into photomultiplier tubes (PMT) situated along the outer radii. The readout of it is organized in a projective geometry as illustrated in Figure 3.7. In the barrel and the extended barrel sections, most of the hadronic energy is captured by the first or last two layers, which account for about 5.5 or 6 out of a total of 7 hadronic interaction lengths.

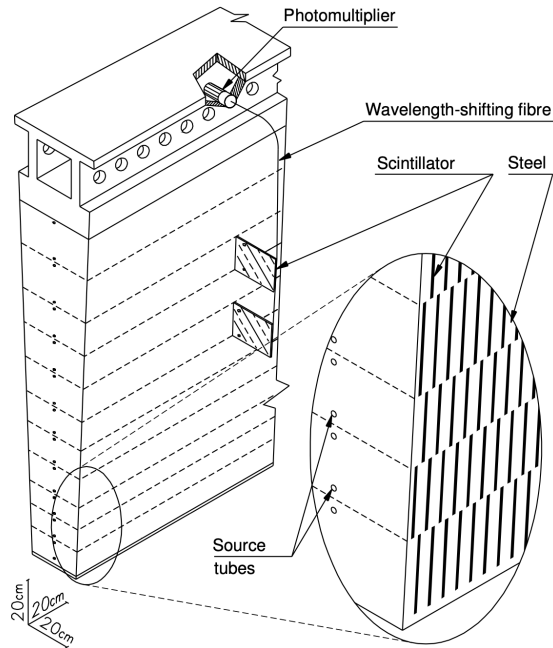


Fig. 3.7: A depiction of a tile calorimeter module, featuring interleaved steel absorbers, scintillating tiles, and PMT readout. Calibration source tubes, used to pass radioactive Cesium sources, are also indicated [14].

For the more forward regions, they are instrumented with LAr sampling calorimeters instead of scintillators because they are exposed to higher radiation than the barrel regions. Two calorimeters were designed to meet this purpose: the hadronic end-cap calorimeter (HEC) which provides a calorimetric coverage in the range of $1.5 < |\eta| < 3.2$ and the forward calorimeter (FCal) system which

covers the range of $3.1 < |\eta| < 4.9$.

The HEC consists of two wheels per end-cap, situated behind the EM end-cap calorimeter at $z = 4.28$ m (front) and $z = 5.13$ m (back). The HEC is composed of layers of copper plates interleaved with 8.5 mm LAr gaps, providing the active medium for this sampling calorimeter. To ensure stability, the readout structure is obtained by dividing the gaps into separate drift zones that are dedicated to the readout electrodes. The FCal also shares the end-cap cryostat, starting at $z = 4.7$ m. As shown in Figure 3.8, it consists of three layers in the z direction, an electromagnetic layer (FCal 1) and two hadronic layers (FCal 2 & FCal 3). All the three layers use LAr as the active medium, but FCal 1 uses copper as its absorber because of its heat removal properties, while FCal 2 and FCal 3 use tungsten absorbers to provide a high containment and minimisation of the lateral spread of hadronic showers. These detectors operate on the same principles as the EM calorimeter and share its readout electronic design.

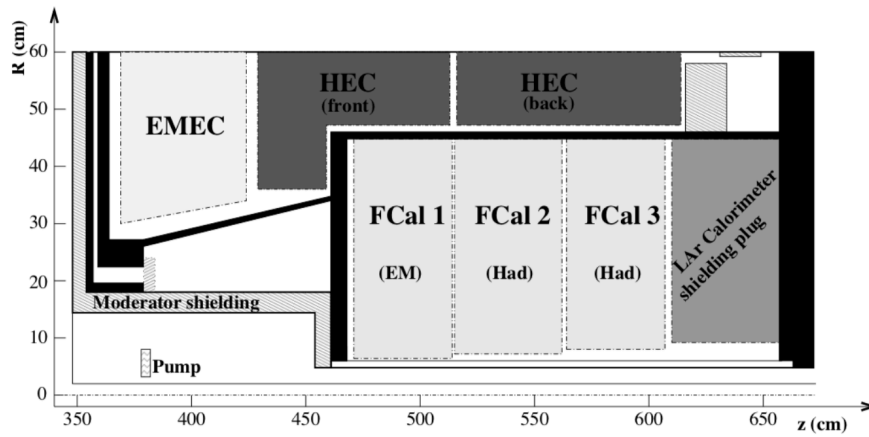


Fig. 3.8: A diagram showing the HEC and FCal systems, along with part of the EM calorimeter [15].

3.2.4 Muon spectrometer

High-momentum muons are amongst the most promising and robust signatures of physics at the LHC. Due to its small cross-section for interactions, muons leave only a small fraction of their energy without being contained in the calorimeter, therefore a muon spectrometer (MS) responsible for detecting high-momentum muons is placed in the outermost layer of the ATLAS. The MS is based on the magnetic deflection of muon tracks, permitting a precise measurement of its momentum. The bending of the muon trajectories is provided by a large superconducting air-core toroid magnet system, where a large barrel torioid covers the range of $|\eta| < 1.4$ and end-cap torioid systems cover $1.6 < |\eta| < 2.7$. The mo-

mentum of the muon is measured at three separate points along its trajectory, allowing for tracking measurements.

The MS is composed by 4000 muon chambers, classified with 4 different flavors: Thin Gap Chambers (TGC) and Resistive Plate Chambers (RPC) which allow for the precise measurement the muon tracks as they traverse the MS, Monitored Drift Tubes (MDT) and Cathode Strip Chambers (CSC) which allow for accurate assignment of a passing muon to a specific pp bunch crossing. All 4 flavor detectors exist in the barrel and end-cap sections of the MS and there are typically at least three layers of precision-type chambers over the entire $|\eta|$ range of the MS in order to allow for the measurement of the muon tracks [92].

3.2.5 Trigger and data acquisition

At a beam luminosity of $10^{34} \text{cm}^{-2} \text{s}^{-1}$, the LHC provides about 20 collisions per bunch crossing every 25 ns, which yields about 1 billion collisions per second. Nevertheless, the vast majority of such interactions will end up creating processes that are unlikely to contain interesting physics, and most of the events therefore don't need to be recorded at all. In order to reduce the data rate to a manageable quantity while ensuring that the events recorded are those containing interesting physics, a two-stage trigger system is implemented in ATLAS during Run 2 for online processing, selecting and classifying events of interest for offline analysis. An overview of the trigger system is shown in Figure 3.9.

The preliminary phase of the trigger system is a hardware-based low-level trigger, referred to as the Level-1 (L1) trigger, which uses custom electronics to trigger on reduced-granularity information from the calorimeter and muon detector. It performs the first level selection, reducing the initial event rate of 40 MHz to a target of 100 kHz with an expected storage of 1.5 GB per second. The L1 trigger performs a rough identification of certain physics objects: jets, leptons and photons. The electrons and photons are triggered based on energy deposition in the EM calorimeter in $|\eta| < 2.5$ region, while jet candidates are provided by the hadronic calorimeter in η - ϕ plane. Muon-based L1 triggers are based on coincidences hits along the layers of the MS, forming projective roads consistent with high- p_T muons.

The candidate events selected by the L1 trigger are forwarded to the second stage software-based trigger, the High-Level Trigger (HLT). A typical reconstruction sequence utilize dedicated fast trigger algorithms to provide early rejection, followed by more precise and more CPU-intensive. The HLT software is mainly based on the offline software Athena [93] which is configured by a set of properties that can be defined during the configuration stage of the application. The

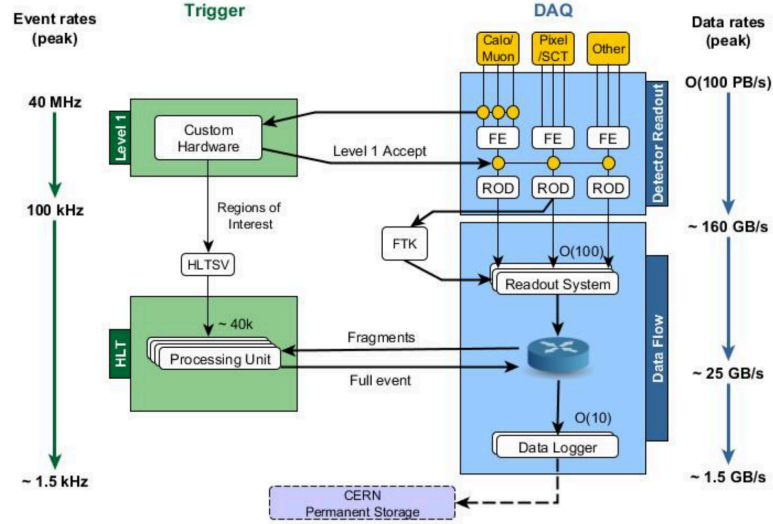


Fig. 3.9: Summary of the ATLAS Run 2 trigger and data acquisition system. Data from the muon spectrometer (MS) and calorimeters are processed by the Level-1 (L1) trigger, which reduces the data rate from 40 MHz to 100 kHz. The L1 trigger-selected data are buffered in the readout drivers, allowing algorithms in the High-Level Trigger (HLT) to sample them. Events accepted by the HLT are sent to permanent storage through the Data Logger [16].

acceptance rate of the HLT is about 1.2 kHz with an average physics throughput to permanent storage of 1.2 GB per second. The event accepted by the HLT will be exported to the Tier-0 facility at CERN's computing centre.

CHAPTER 4

Object Reconstruction and Particle Identification

4.1 Object Reconstruction

4.1.1 Electron reconstruction

In particle interactions within detectors, an electron can lose a significant fraction of its energy via bremsstrahlung while traversing the material. The radiated photon may subsequently convert into an electron-positron pair, which can further interact with the detector material. These secondary particles, including positrons, electrons, and photons, are typically emitted in a highly collimated manner and are generally reconstructed within the same electromagnetic cluster. These interactions may take place within the inner-detector volume or even within the beam pipe, leading to the generation of multiple tracks in the inner detector. Alternatively, these interactions can occur downstream of the inner detector, influencing only the shower development in the calorimeter. Consequently, it is feasible to produce and associate multiple tracks with a singular electromagnetic cluster, all originating from the same primary electron.

The reconstruction of electron candidates within the kinematic range covered by the high-granularity electromagnetic calorimeter and the inner detector relies on three primary components characterizing the electron signature: localized clusters of energy deposits within the electromagnetic calorimeter, charged-particle tracks identified in the inner detector, and precise matching in $\eta \times \phi$ space of the tracks to the clusters to form the final electron candidates. Therefore, the electron reconstruction process in the ATLAS detector's precision region ($|\eta| < 2.47$) follows these steps, as outlined below. Figure 4.1 provides a schematic overview of the elements involved in the reconstruction and identification process.

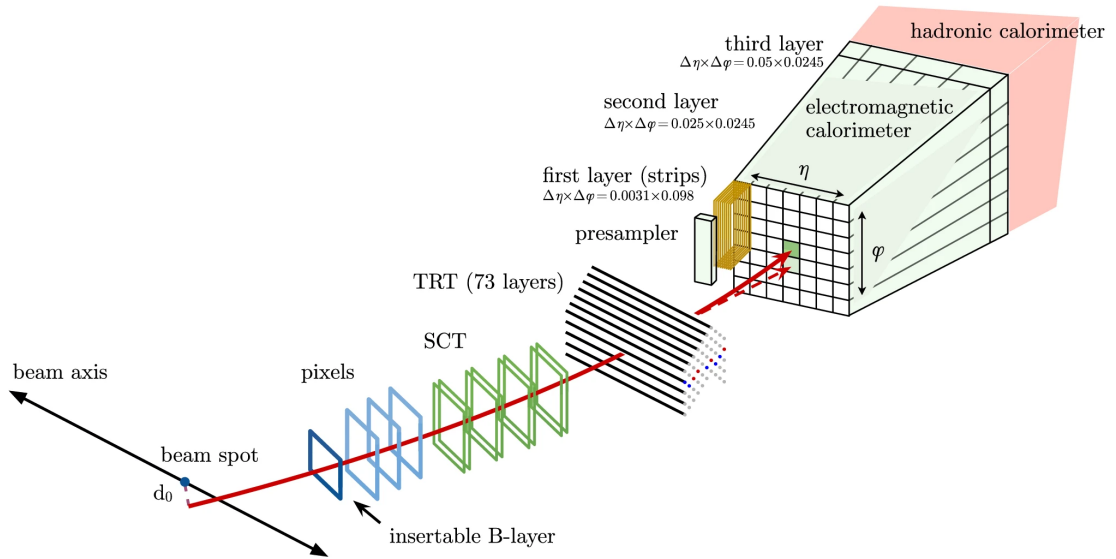


Fig. 4.1: A schematic diagram depicting the path of an electron through the detector. The red line represents the hypothetical trajectory of an electron as it passes through the tracking system (starting with pixel detectors, followed by silicon-strip detectors, and finally the TRT) before reaching the electromagnetic calorimeter. The dashed red line illustrates the path of a photon generated by the electron's interaction with the material in the tracking system [17].

4.1.2 Photon reconstruction

Initial photon candidates can be reconstructed as either converted or unconverted. A converted photon object is characterized by an EM topo-cluster matched to one or more conversion vertices. The process of reconstructing these conversion vertices adheres to the methods outlined in Refs. [20, 94, 95]. Two types of conversion vertices are utilized: those formed by two tracks with opposite charges and those formed by single tracks without hits in the innermost sensitive layers. The matching of the conversion vertices to the EM topo-cluster is accomplished by extrapolating the conversion candidate to the second sampling layer of the calorimeter. The difference between the extrapolated η and ϕ coordinates of the conversion vertex and the EM topo-cluster center must be less than 0.05 or 0.1 for double- or single-track conversions, respectively. Unconverted photons are identified from EM topo-clusters not associated with an electron track or a conversion vertex.

Using these initial photon candidates, the final EM clusters are constructed from all clusters associated with the candidates. If a candidate has undergone bremsstrahlung radiation, which commonly occurs in the bending plane, it may be reconstructed as two clusters. This situation arises in about 10% of cases, mainly in the forward and transition regions [20]. Consequently, nearby EM topo-clusters are merged to form the final EM cluster. Beginning with the highest-energy EM

cluster, adjacent clusters within $\Delta\eta \times \Delta\phi = 0.075 \times 0.125$ of their respective barycenters are merged with the initial cluster unless they have already been used. For converted photons, additional clusters within $\Delta\eta \times \Delta\phi = 0.125 \times 0.3$ are considered if their best-matched track or conversion vertex coincides with the original cluster. These final EM clusters, referred to as superclusters, constitute the photon objects [20]. Following initial position corrections and energy calibrations to the merged EM clusters, the procedures for track and conversion vertex matching are reiterated to finalize the photon objects. Their energies are then recalibrated using the methods described in Refs. [20, 96].

4.1.3 Muon reconstruction

When a muon candidate is reconstructed, five parameters are derived from the track fit: $M = (d_0, z_0, \phi, \theta, q/p)$ [97]. Initially, a muon traversing the ATLAS detector passes through the Inner Detector (ID), bending in the ϕ direction due to a 2 T solenoid magnetic field. The ID track, which has highly precise hits near the Interaction Point (IP), helps constrain the impact parameters d_0 and z_0 , as well as the angles ϕ and θ . After traversing the electromagnetic and hadronic calorimeters, the muon enters the Muon Spectrometer (MS) and bends along the θ direction due to a toroidal magnetic field. The MS track benefits from superior q/p resolution owing to its longer lever arm. Within the ATLAS detector, four muon reconstruction algorithms are available:

- Combined (CB) muons: Obtained through a global refit of the ID and MS tracks.
- Segment-tagged (ST) muons: Comprising a fitted ID track and an MS segment.
- Calorimeter-tagged (CT) muons: Including a fitted ID track and an energy deposit in the calorimeters.
- Extrapolated (ME) muons: Consisting solely of an MS track.

Figure 4.2 illustrates the four aforementioned muon reconstruction algorithms.

4.1.4 Jet reconstruction and calibration

The primary jet identification algorithm utilized by the ATLAS collaboration is the anti- k_t algorithm [98], which operates with a distance parameter of $R = 0.4$. Various entities can serve as inputs to this algorithm, including calorimeter energy deposits, inner detector tracks [99], or a combination of both [100]. For jet identification in Monte Carlo simulations, stable particles with a lifetime exceeding

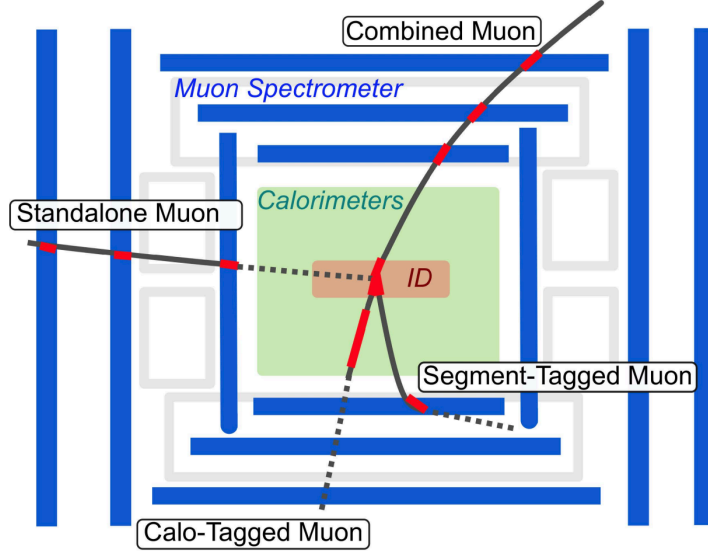


Fig. 4.2: Reconstruction techniques implemented in the ATLAS detector.

10 ps, excluding muons and neutrinos, are employed.

Jets reconstructed from tracks, known as track jets, exhibit minimal dependence on pile-up activities as only tracks from the primary vertex are considered. Nonetheless, the ATLAS tracker acceptance limits track jet reconstruction to $|\eta| < 2.5$. Consequently, ATLAS analyses predominantly utilize jets reconstructed from calorimeter deposits, referred to as calorimeter jets.

The inputs for calorimeter jets reconstruction are the topologically clustered calorimeter cells, or topo-clusters [101]. The topological clustering algorithm aggregates cells with significant energy deposits to effectively suppress noise. The noise in calorimeter cells is calculated as the quadratic sum of the measured electronics and pile-up noise. Clustering starts with seed cells where the energy deposits exceed 4σ , and neighboring cells are iteratively included in the topo-cluster if their energy exceeds 2σ . This process continues until no more cells can be added. Ultimately, the cluster splitting algorithm separates topo-clusters based on local energy maxima to avoid overlap, and only those clusters with positive energy are utilized for jet reconstruction.

Calorimeter cells' energy is measured using electrons at test beams, and the Local Cell Weighting (LCW) calibration [102] can be applied to clusters classified as hadronic to account for different detector responses to electromagnetic and hadronic particles. This calibration enhances jet energy resolution and is derived from Monte Carlo simulations of single pion events.

The jet energy scale (JES) calibration [103] adjusts the reconstructed jets' energy scale to match simulated truth jets. Multiple correction factors are developed

for jets reconstructed using both EM and LCW topo-clusters. The JES calibration incorporates origin correction, pile-up correction, and absolute detector response correction based on Monte Carlo simulations, along with global sequential correction and residual in situ calibration.

The origin correction aligns the jet’s four-momentum to the hard-scatter primary vertex instead of the detector center, maintaining the jet energy constant. Proton-proton collisions at $\sqrt{s} = 13$ TeV with reduced bunch spacing (25 ns) in Run-2 increased pile-up, impacting the measured jet transverse momentum. A two-step procedure mitigates this effect by first removing pile-up’s average energy density and area contribution and then applying a residual correction to address the jet’s remaining pile-up dependence on reconstructed primary vertices (N_{PV}) and average interactions per bunch crossing ($\langle\mu\rangle$). Figure 4.3 (a) demonstrates the pile-up correction performance.

Jet energy scale and η calibration adjust reconstructed jet energy to particle-level scales, accounting for calorimeter response differences using Monte Carlo simulations. Additionally, they correct any biases due to transitions between calorimeter regions and granularity differences. Figure 4.3 (b) shows the detector η response for jets with different simulated truth energies.

The Global Sequential Correction (GSC) [104] aims to reduce jet response dependence on the initiated-jet parton’s flavor. It uses jet properties such as energy in the hadronic calorimeter’s third layer, p_T -weighted transverse distance in $\eta - \phi$ space, and associated tracks and muon segments to correct jet response, considering punch-through effects. The in situ JES calibration applies to data-measured jets, using the jet response difference between data and Monte Carlo simulations with transverse momentum balance of jets and reference objects.

Jets from the central detector region ($|\eta_{\text{det}}| < 0.8$) are used to derive residual calibrations for forward region jets ($0.8 < |\eta_{\text{det}}| < 4.5$) through dijet events (η -intercalibration). Figure 4.4 (a) presents the relative jet response measured using Run-2 ATLAS data and Monte Carlo simulations across detector pseudorapidity. The lower panel depicts the η -intercalibration correction.

Two methods, Z+jet and γ +jet events, calibrate jets up to 950 GeV using perfect transverse momentum balance of jets and reference bosons or photons in the $2 \rightarrow 2$ process. However, this method may be affected by additional parton radiation, leading to energy loss outside the considered jet cone. The Missing Projection Fraction method uses the event’s full hadronic recoil instead of a single reconstructed jet, reducing sensitivity to jet definition and out-of-cone radiation. These complementary methods ensure the compatibility of measured responses.

High- p_T jets (up to 2 TeV) are calibrated using multiple lower- p_T jets (Multijet Balance). Figure 4.4 (b) shows the combined in situ corrections across the jet

p_T measured using Z+jet, γ +jet, and multijet events. The listed calibrations are applied sequentially, with statistical and systematic uncertainties propagated through the calibration scheme.

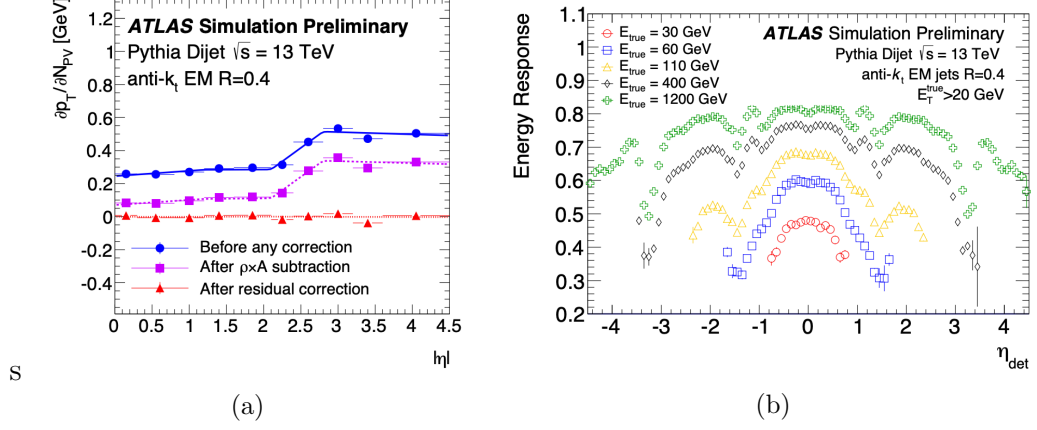


Fig. 4.3: (a) The variation of the EM scale jet transverse momentum with N_{PV} as a function of $|\eta|$, shown before pile-up corrections (blue), after applying the area-based correction (violet), and following the residual correction (red). (b) The average jet energy response as a function of detector pseudorapidity for various truth energy levels [18].

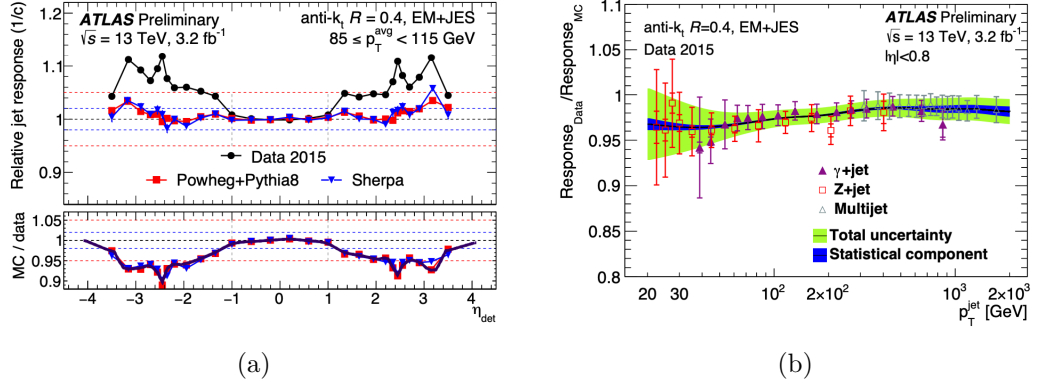


Fig. 4.4: (a) Relative jet response as a function of detector pseudorapidity in a specific jet p_T bin, based on ATLAS Run-2 data and Monte Carlo simulations. The lower panel illustrates the η -intercalibration correction. (b) Combined in situ corrections as a function of jet p_T , derived from Z+jet, γ +jet, and multijet events. The shaded bands represent the total uncertainty along with its statistical component. Adapted from [19].

4.1.5 Missing transverse momentum reconstruction

The reconstruction of missing transverse momentum, denoted as E_T^{miss} , in the ATLAS detector [105] is fundamentally derived from two main components. The

first component originates from the signals associated with hard events, which encompass fully reconstructed and calibrated particles and jets, collectively referred to as hard objects. This collection includes various reconstructed particles such as electrons, photons, τ -leptons, and muons. Specifically, muons are identified through the analysis of tracks from both the inner detector (ID) and the muon system (MS), while electrons and τ -leptons are identified by integrating signals from the calorimeter with track information. Photons and jets primarily rely on calorimetric signals for reconstruction, potentially enhanced by data from reconstructed tracks.

The second component contributing to E_T^{miss} is derived from soft-event signals, which comprise the reconstructed tracks of charged particles associated with the hard scatter vertex, as defined in Appendix A. Importantly, these soft signals are not directly linked to the hard objects.

The calculation of missing transverse momentum results in a set of observables, which are derived from the transverse momentum components $p_{x(y)}$ of the various contributing objects. The components of missing transverse momentum, $E_{x(y)}^{\text{miss}}$, are crucial inputs for a majority of these observables, expressed mathematically as:

$$E_{x(y)}^{\text{miss}} = - \sum_{i \in \{\text{hard objects}\}} p_{x(y),i} - \sum_{j \in \{\text{soft signals}\}} p_{x(y),j}. \quad (4.1)$$

The collection of observables derived from $E_{x(y)}^{\text{miss}}$ encompasses the following key quantities:

$$E_T^{\text{miss}} = (E_x^{\text{miss}}, E_y^{\text{miss}}), \quad (4.2)$$

$$E_T^{\text{miss}} = |E_T^{\text{miss}}| = \sqrt{(E_x^{\text{miss}})^2 + (E_y^{\text{miss}})^2}, \quad (4.3)$$

$$\phi^{\text{miss}} = \tan^{-1}(E_y^{\text{miss}}/E_x^{\text{miss}}). \quad (4.4)$$

The vector E_T^{miss} encapsulates both the magnitude and direction of missing transverse momentum within the transverse plane, characterized by the azimuthal angle ϕ^{miss} . By definition, E_T^{miss} remains non-negative. Nonetheless, in experimental contexts where complete reconstruction of all pertinent transverse momentum p_T from the hard-scatter interaction is not feasible, as indicated in Equation 4.1, a systematic bias emerges. This bias arises from the fact that the reconstructed p_T contributions are influenced by the finite resolution of the detector. Consequently, even in final states that do not intrinsically possess genuine missing transverse momentum—such as that caused by undetectable particles—there exists an inclination towards observing non-zero values of E_T^{miss} .

The scalar sum of all transverse momenta, expressed as $\sum p_T = |\sum \mathbf{p}_T|$, encompasses the contributions from various objects that are integral to the reconstruction of E_T^{miss} . This scalar sum is mathematically represented as:

$$\sum E_T = \sum_{i \in \{\text{hard objects}\}} p_{T,i} + \sum_{j \in \{\text{soft signals}\}} p_{T,j}. \quad (4.5)$$

In the framework of E_T^{miss} reconstruction, the scalar sum $\sum E_T$ is computed alongside the sum expressed in Equation 4.1, as well as the quantities defined for E_T^{miss} in Equations 4.3 to 4.4. This calculation serves as a valuable metric for assessing the energy scale of hard-scatter events in the transverse plane, effectively providing insights into event activity relevant to physics analyses and evaluations of E_T^{miss} reconstruction performance.

Within the ATLAS framework, the adaptability required to recalibrate both E_T^{miss} and $\sum E_T$ in response to varying analytical needs for a given event is facilitated by employing dedicated variables associated with specific object contributions. In this methodology, the complete vector E_T^{miss} represents the vectorial sum of the missing transverse momentum components $E_T^{\text{miss},p}$, where $p \in \{e, \gamma, \tau_{\text{had}}, \mu, \text{jet}\}$. These components are reconstructed from the transverse momentum vectors $\mathbf{p}_T = (p_x, p_y)$ of identified particles and jets, combined with the corresponding soft term $E_T^{\text{miss},\text{soft}}$, which is derived from the soft-event signals. This comprehensive approach results in:

$$E_T^{\text{miss}} = - \underbrace{\sum_{\text{selected electrons}} p_T^e - \sum_{\text{accepted photons}} p_T^\gamma - \sum_{\text{accepted } \tau_{\text{had}}} p_T^{\tau_{\text{had}}} - \sum_{\text{selected muons}} p_T^\mu - \sum_{\text{accepted jets}} p_T^{\text{jet}}}_{\text{hard term}} - \underbrace{\sum_{\text{unused tracks}} p_T^{\text{track}}}_{\text{soft term}}. \quad (4.6)$$

where $E_T^{\text{miss},e}$, $E_T^{\text{miss},\gamma}$, $E_T^{\text{miss},\tau_{\text{had}}}$, $E_T^{\text{miss},\mu}$, $E_T^{\text{miss},\text{jet}}$, and $E_T^{\text{miss},\text{soft}}$ represent the contributions from the selected electrons, identified photons, accepted τ -leptons, reconstructed muons, accepted jets, and unused tracks, respectively.

The observables E_T^{miss} and ϕ^{miss} can be computed according to Equations 4.3 and 4.4, providing a comprehensive representation of the overall missing transverse momentum derived from E_T^{miss} as well as for each individual term detailed in Equation 4.6. In the reconstruction process of E_T^{miss} , contributions are determined by a combination of analysis-dependent selection criteria and potential exclusions stemming from applied signal overlap resolutions. Notably, contributions from muons and electrons typically bypass the signal overlap resolution and are thereby

exclusively dictated by the specific selection criteria. The term “unused tracks” in Equation 4.6 pertains to tracks that are linked to the hard-scatter vertex but not associated with any hard object. Additionally, neutral particle signals from the calorimeter are significantly affected by pile-up contributions and are therefore excluded from the soft term.

Subsequently, $\sum E_T$ is computed as the scalar sum of the transverse momenta from the hard objects involved in the E_T^{miss} reconstruction along with the contributions from the soft term:

$$\Sigma E_T = \underbrace{\sum_{\text{selected electrons}} p_T^e + \sum_{\text{accepted photons}} p_T^\gamma + \sum_{\text{accepted } \tau\text{-leptons}} p_T^{\tau^{\text{had}}} + \sum_{\text{selected muons}} p_T^\mu + \sum_{\text{accepted jets}} p_T^{\text{jet}}}_{\text{hard term}} + \underbrace{\sum_{\text{unused tracks}} p_T^{\text{track}}}_{\text{soft term}}. \quad (4.7)$$

The hard component of both E_T^{miss} and $\sum E_T$ is characterized by a negligible dependence on pile-up effects, as it incorporates only fully calibrated objects. This calibration process encompasses pile-up corrections, resulting in the exclusion of objects identified as originating from pile-up interactions. Furthermore, the intentional selection of tracks solely associated with the hard-scatter vertex for the soft component significantly reduces pile-up contributions to this term. This methodology enhances the reliability of the E_T^{miss} measurement, ensuring that the reconstructed transverse momentum accurately reflects authentic physical processes rather than artifacts arising from overlapping events.

4.2 Particle Identification

4.2.1 Electron identification

Prompt electrons that enter the central region of the detector ($|\eta| < 2.47$) are selected through a likelihood-based (LH) identification approach. The inputs to the LH algorithm include measurements from the tracking system, the calorimeter system, and integrated quantities that merge both tracking and calorimeter data. These various inputs are outlined in Table 4.1, and the components of the quantities mentioned are schematically illustrated in Figure 4.1. The methodology employed for the LH identification closely mirrors that used for electron LH identification during Run 1 (2010–2012); however, several critical distinctions exist. In anticipation of data-taking at higher center-of-mass energies and under altered detector conditions, it was necessary to construct probability density functions

(pdfs) based on simulated events instead of data events. Subsequent corrections were made to the resulting distributions to account for any mismodelling. Additionally, the efficiency was smoothed as a function of E_T and the likelihood was modified to extend its applicability to electrons with $E_T > 300$ GeV.

The electron likelihood (LH) is predicated upon the product of probabilities for the signal, L_S , and for the background, L_B , across n probability density functions, P :

$$L_{S(B)}(\mathbf{x}) = \prod_{i=1}^n P_{S(B),i}(x_i), \quad (4.8)$$

where $\mathbf{x}$ represents the vector of various quantities outlined in Table 4.1. $P_{S,i}(x_i)$ is the value of the signal pdf for quantity i at value x_i and $P_{B,i}(x_i)$ is the respective value for the background pdf. The signal corresponds to prompt electrons, while the background is typified by jets that replicate the signature of prompt electrons, electrons arising from photon conversions in the detector material, and non-prompt electrons from hadron decay containing heavy flavors. Correlations in the quantities selected for the LH are not considered.

A discriminant, d_L , is then constructed for each electron candidate as:

$$d_L = \frac{L_S}{L_S + L_B}, \quad (4.9)$$

The LH identification is predicated on this discriminant. The discriminant d_L exhibits a pronounced peak at unity (signal) and zero (background), which presents challenges in selecting operational points due to the necessity of extremely fine binning. To address this, an inverse sigmoid function 4.10 is utilized to remap the distribution of the discriminant:

$$d'_L = \tau^{-1} \ln \left(\frac{d_L}{1 - d_L} \right), \quad (4.10)$$

Here, the parameter τ is calibrated to 15 [106] as per reference. This transformation stabilizes the range of discriminant values, which now lies between zero and infinity, facilitating the definition of threshold values for signal discrimination. Electron candidates with a transformed discriminant, d'_L , exceeding a set threshold are categorized as signal. A representation of the distribution of the transformed discriminant for signal and background is depicted in Figure 4.5, underscoring the distinction between signal and background within this single metric.

The adoption of a likelihood-based (LH) methodology for electron identification provides two significant advantages over conventional cut-based (selection-criteria) identification approaches. First, an electron that fails to meet a specific selection criterion in a cut-based approach may still be recognized under the LH-

Table. 4.1: Types and descriptions of the variables utilized in electron identification.

Type	Description	Name	Rejects			Usage
			LF	γ	HF	
Hadronic leakage	Ratio of E_T in the first layer of the hadronic calorimeter to E_T of the EM cluster (used over the range $\ \eta\ < 0.8$ or $\ \eta\ > 1.37$)	R_{had1}	x	x		LH
	Ratio of E_T in the hadronic calorimeter to E_T of the EM cluster (used over the range $0.8 < \ \eta\ < 1.37$)	R_{had}	x	x		LH
Third layer of EM calorimeter	Ratio of the energy in the third layer to the total energy in the EM calorimeter. This variable is only used for $E_T < 80\text{GeV}$, due to inefficiencies at high E_T , and is also removed from the LH for $\ \eta\ > 2.37$, where it is poorly modelled by the simulation.	f_3	x			LH
Second layer of EM calorimeter	Lateral shower width, $\sqrt{(\Sigma E_i \eta_i^2) / (\Sigma E_i) - ((\Sigma E_i \eta_i) / (\Sigma E_i))^2}$, where E_i is the energy and η_i is the pseudorapidity of cell i and the sum is calculated within a window of 3×5 cells	$w_{\eta 2}$	x	x		LH
	Ratio of the energy in 3×3 cells over the energy in 3×7 cells centred at the electron cluster position	R_ϕ	x	x		LH
	Ratio of the energy in 3×7 cells over the energy in 7×7 cells centred at the electron cluster position	R_η	x	x	x	LH
First layer of EM calorimeter	Shower width, $\sqrt{(\Sigma E_i (i - i_{\text{max}})^2) / (\Sigma E_i)}$, where i runs over all strips in a window of $\Delta\eta \times \Delta\phi \approx 0.0625 \times 0.2$, corresponding typically to 20 strips in η , and i_{max} is the index of the highest-energy strip, used for $E_T > 150\text{GeV}$ only	w_{stot}	x	x	x	C
	Ratio of the energy difference between the maximum energy deposit and the energy deposit in a secondary maximum in the cluster to the sum of these energies	E_{ratio}	x	x		LH
	Ratio of the energy in the first layer to the total energy in the EM calorimeter	f_1	x			LH
Track conditions	Number of hits in the innermost pixel layer	n_{Blayer}		x		C
	Number of hits in the pixel detector	n_{Pixel}		x		C
	Total number of hits in the pixel and SCT detectors	n_{Si}		x		C
	Transverse impact parameter relative to the beam-line	d_0		x	x	LH
	Significance of transverse impact parameter defined as the ratio of d_0 to its uncertainty	$\ d_0/\sigma(d_0)\ $		x	x	LH
	Momentum lost by the track between the perigee and the last measurement point divided by the momentum at perigee	$\Delta p/p$	x			LH
TRT	Likelihood probability based on transition radiation in the TRT	eProbabilityHT	x			LH
Track-cluster matching	$\Delta\eta$ between the cluster position in the first layer and the extrapolated track	$\Delta\eta_1$	x	x		LH
	$\Delta\phi$ between the cluster position in the second layer of the EM calorimeter and the momentum-rescaled track, extrapolated from the perigee, times the charge q	$\Delta\phi_{\text{res}}$	x	x		LH
	Ratio of the cluster energy to the track momentum, used for $E_T > 150\text{GeV}$ only	E/p	x	x		C

based framework, as this method aggregates information from multiple discriminative variables. Second, discriminative variables with overlapping distributions, which might compromise the efficiency of cut-based identification, can be seamlessly integrated into the LH-based system without any loss in performance. Notably, variables such as R_ϕ and f_1 , which are employed in the LH-based identification but are absent in cut-based approaches, are detailed in Table 4.1. Figure 4.6 juxtaposes the distributions of these variables for prompt electrons against the background, highlighting the superior discriminative capability of the LH-based approach.

The implementation of isolation criteria is tailored to the requirements of specific physics analyses, balancing the precise identification of prompt electrons,

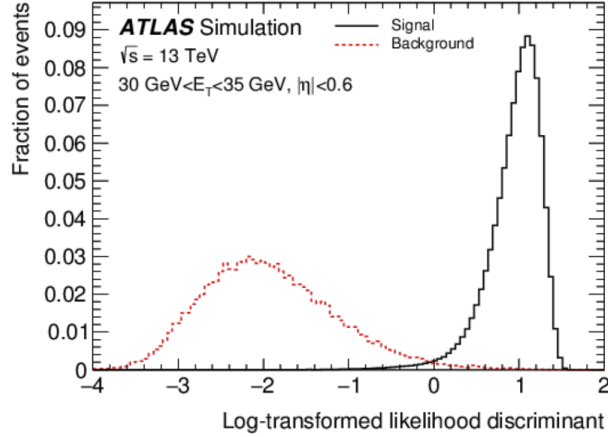


Fig. 4.5: The transformed likelihood-based identification discriminant d'_L for reconstructed electron candidates with high-quality tracks within the range of $30 \text{ GeV} < E_T < 35 \text{ GeV}$ and $|\eta| < 0.6$. The black histogram corresponds to prompt electrons from a $Z \rightarrow ee$ simulation sample, while the red dashed-line histogram represents background events from a generic two-to-two process simulation. Both histograms are normalized to have unit area.

whether isolated or in dense environments, with the effective rejection of electrons originating from heavy-flavour decays or misidentified light hadrons. The various electron-isolation working points employed in ATLAS are detailed in Table 4.2.

Isolation working points can be defined either by targeting a fixed efficiency value or by applying fixed cuts on isolation variables. The Gradient working point aims for an efficiency of 90% at $p_T = 25 \text{ GeV}$ and 99% at $p_T = 60 \text{ GeV}$, consistent across different η regions. The requirements for E_T^{cone20} and $p_T^{\text{varcone20}}$ for this working point are derived from $J/\psi \rightarrow ee$ ($E_T < 15 \text{ GeV}$) and $Z \rightarrow ee$ ($E_T > 15 \text{ GeV}$) MC simulations and tag-and-probe identification criteria. The other three working points, HighPtCaloOnly, Loose, and Tight, utilize fixed cuts on calorimeter and/or track isolation variables.

Table. 4.2: Descriptions of the electron isolation working points and the corresponding isolation efficiency ϵ . For the Gradient working point, p_T is measured in GeV. All working points apply a cone size of $\Delta R = 0.2$ for calorimeter isolation and $\Delta R_{\text{max}} = 0.2$ for track isolation.

Working point	Calorimeter isolation	Track isolation
Gradient	$\epsilon = 0.1143 \times p_T + 92.14\%$ (with E_T^{cone20})	$\epsilon = 0.1143 \times p_T + 92.14\%$ (with $p_T^{\text{varcone20}}$)
HighPtCaloOnly	$E_T^{\text{cone20}} < \max(0.015 \times p_T, 3.5 \text{ GeV})$	–
Loose	$E_T^{\text{cone20}}/p_T < 0.20$	$p_T^{\text{varcone20}}/p_T < 0.15$
Tight	$E_T^{\text{cone20}}/p_T < 0.06$	$p_T^{\text{varcone20}}/p_T < 0.06$

Figure 4.7 displays the electron isolation efficiency as a function of electron E_T and η , as well as the number of interactions per bunch crossing for the isolation working points summarized in Table 4.2. The pile-up correction applied

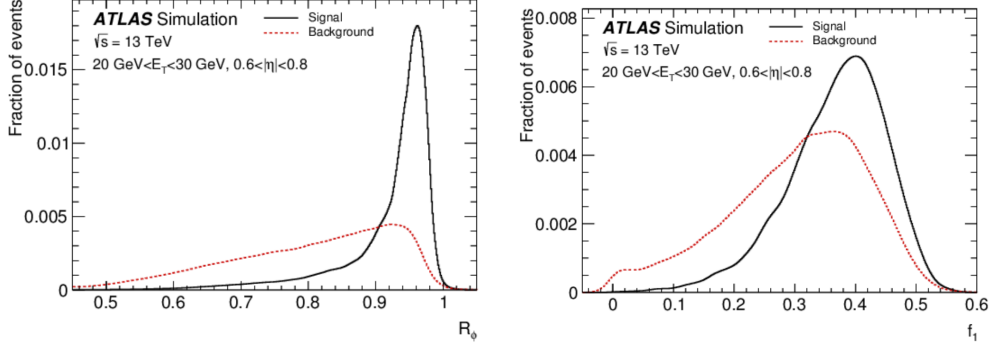


Fig. 4.6: Examples of the distributions for two variables, R_ϕ (top) and f_1 (bottom), both defined in Table 4.1, are presented for $20 \text{ GeV} < E_T < 30 \text{ GeV}$ and $0.6 < |\eta| < 0.8$. These variables would be inefficient in a cut-based identification approach but possess strong discriminating power against background, making them valuable for improving likelihood-based identification. In each plot, the red dashed line represents the distribution from a background simulation sample, while the black solid line corresponds to a $Z \rightarrow ee$ simulation sample. These distributions, for reconstructed electron candidates, are shown prior to any identification cuts, smoothed using an adaptive KDE, and corrected for differences in offsets or widths between data and simulation distributions.

to the calorimeter isolation reduces its dependence by approximately a factor of five. These results are obtained using a sample enriched in $Z \rightarrow ee$ events, with electrons fulfilling the Medium selection criteria from the likelihood-based electron identification. The methodology for computing the isolation efficiency and the associated uncertainties is detailed in Ref. [107]. For the Gradient working point, a significant efficiency jump is observed at the transition point of 15 GeV due to its p_T -dependent efficiency. Optimization is performed for $J/\psi \rightarrow ee$ events below 15 GeV and $Z \rightarrow ee$ events above 15 GeV. The Tight working point offers the highest background rejection below 60 GeV and the most pronounced reduction in η -shape dependence. HighPtCaloOnly is optimized for high- E_T regions ($E_T > 100 \text{ GeV}$). Both the Gradient and Tight working points demonstrate the highest pile-up rejection, with isolation efficiency decreasing from approximately 95% at low $\langle \mu \rangle$ to about 85% when $\langle \mu \rangle$ is around 70–80.

Overall differences between data and MC simulations are below 1–5%, with the largest deviation observed for HighPtCaloOnly in the high- E_T region. For electrons with E_T exceeding 500 GeV, measurements are limited by the number of data events, and results from the E_T bin [300,500] GeV include additional systematic uncertainties varying between 0.1% and 1.7%, depending on the isolation working point. The total scale factor uncertainties range from approximately 5% for electrons with E_T below 7 GeV to less than 0.5% for high E_T .

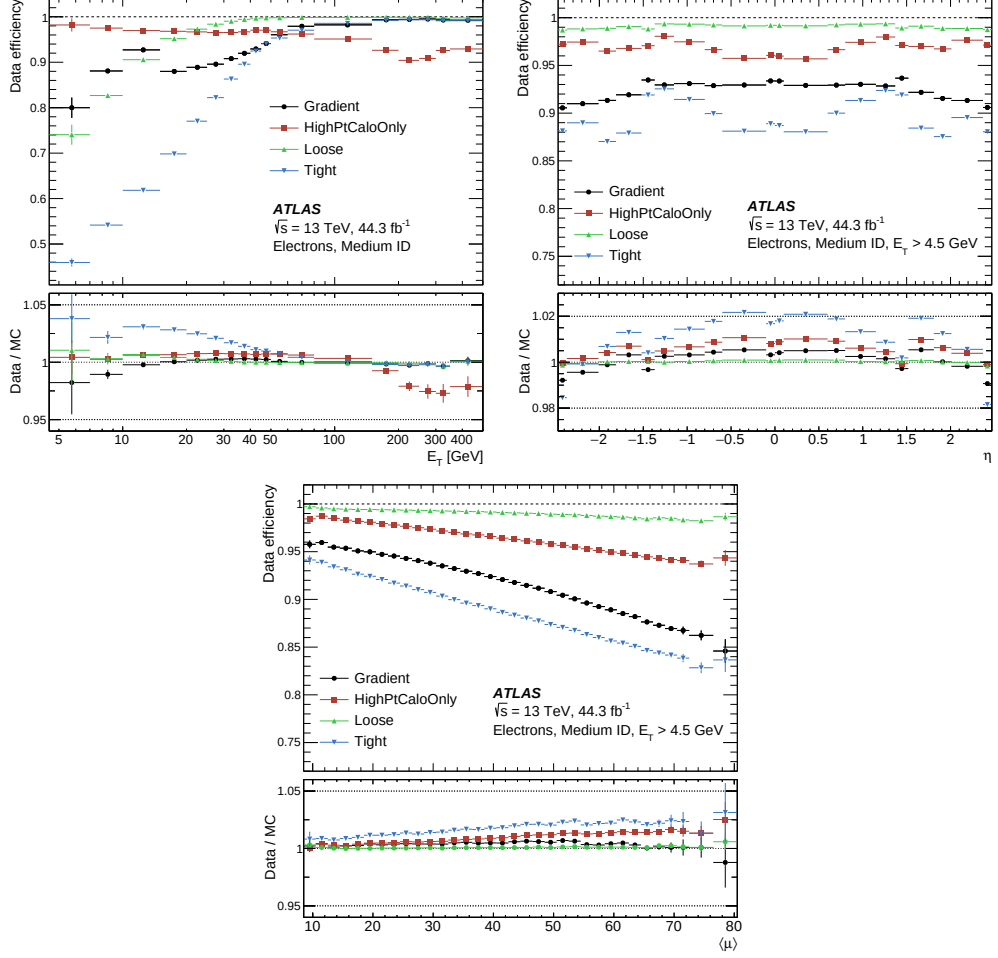


Fig. 4.7: Efficiency of the different isolation working points for electrons from inclusive $Z \rightarrow ee$ events as a function of the electron E_T (top left), electron η (top right) and the number of interactions per bunch crossing $\langle\mu\rangle$ (bottom). The electrons are required to meet the Medium selection from the likelihood-based electron identification. The lower panels show the ratio of efficiencies measured in data and in MC simulations, including statistical and systematic uncertainties.

4.2.2 Photon identification and isolation

Photon identification efficiencies are evaluated separately for converted and unconverted photons across 68 bins defined by photon E_T and η . The bin edges for both photon types are set at $E_T = \{10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 80, 100, 125, 150, 175, 250, 350, \infty\}$ GeV and $\eta = \{0, 0.6, 1.37, 1.52, 1.81, 2.37\}$. No measurements are conducted within the η bin $\{1.37, 1.52\}$, which corresponds to the transition region of the ATLAS calorimeter and is thus excluded from photon analyses.

Photon identification efficiency measurements are executed using three distinct methods as outlined in Ref. [20] and combined to generate correction factors for analyses. All photons are required to meet the Loose isolation criterion as

specified in Ref. [94], meaning photon efficiencies are presented relative to this isolation standard.

Figures 4.8 and 4.9 illustrate the efficiencies obtained through the three measurement methods for unconverted and converted photons, respectively, as functions of p_T across four η regions. The upper panels of these figures display data efficiencies, while the lower panels show the ratio of efficiencies derived from data and those predicted by MC simulation. Before efficiency determination in MC simulation, photon shower shapes are adjusted to better match the data, as described in Ref. [94]. The data-to-MC simulation ratios from the three measurement methods are combined via a weighted average for each E_T - η bin, assuming uncorrelated statistical and systematic uncertainties across methods.

For statistical uncertainties, this method is approximate but generally effective, as the electron extrapolation utilizes an independent data sample, and there is some overlap between radiative Z-boson decay events and the inclusive photon sample, which predominantly consists of photon+jet events.

The combined efficiency ratios' results are displayed in the lower panels of Figures 4.8 and 4.9. The overall uncertainty of the combined ratio varies between 5% at low E_T to about 0.4% at high E_T for unconverted photons, and between 7% (low E_T) to approximately 0.7% (high E_T) for converted photons. The overall improvement is between 30%–40%, slightly exceeding expectations based on statistical increases alone, indicating some systematic uncertainty determinations are statistically limited.

Three photon isolation operating points are defined using requirements on the calorimeter and track isolation variables, as summarized in Table 4.3. For the calorimeter-based photon isolation variables, a discrepancy between the peak positions of their distributions in data and simulation has been observed since Run 1 [108], indicating a misalignment in the simulation of the lateral profile development of electromagnetic showers. Consequently, the photon isolation efficiencies in data and simulation do not match, resulting in scale factors significantly different from 1.

These discrepancies are mitigated by applying data-driven shifts to the calorimeter isolation variables for photons in the simulation. The shifts are determined by fitting the calorimeter isolation variable distribution, using Crystal Ball functions [109], in regions dominated by real photons, in both data and simulation. These fits are conducted in bins of photon η , E_T , and conversion status, separately for E_T^{cone20} and E_T^{cone40} isolation variables. The difference in the fitted peak values between data and simulation defines the shift value, which is then applied to the photon calorimeter isolation values in the simulation. Figure 4.10 illustrates the data-driven shifts obtained with 2017 data and the Pythia8 simulation for the

E_T^{cone20} and E_T^{cone40} isolation variables in two η regions. Figure 4.10 shows the distribution of the E_T^{cone40} isolation variable in 2017 data and simulation, using $Z \rightarrow \ell\ell\gamma$ events after the data-driven shifts are applied.

The photon isolation efficiency is examined in two main signatures: radiative Z decays (valid for $10 < E_T < 100$ GeV) and inclusive photons (used in the $25 \text{ GeV} < E_T < \sim 1.5 \text{ TeV}$ range).

Table. 4.3: Descriptions of the photon isolation working points.

Working point	Calorimeter isolation	Track isolation
Loose	$E_T^{\text{cone20}} < 0.065 \times E_T$	$p_T^{\text{cone20}}/E_T < 0.05$
Tight	$E_T^{\text{cone20}} < 0.022 \times E_T + 2.45 \text{ GeV}$	$p_T^{\text{cone20}}/E_T < 0.05$
TightCaloOnly	$E_T^{\text{cone40}} < 0.022 \times E_T + 2.45 \text{ GeV}$	–

4.2.3 Muon identification and isolation

The reconstruction efficiency of muons in ATLAS is estimated through a method known as Tag & Probe, which utilizes high-statistics samples of $Z \rightarrow \mu^+\mu^-$ and $J/\psi \rightarrow \mu^+\mu^-$ resonances. The “tag” is a muon of Medium quality that triggers the event, while the “probe” is reconstructed by an independent system, such as the calorimeter. The reconstruction efficiency is defined by equation 4.11, as detailed in [22].

$$\epsilon(X) = \epsilon(X|\text{ID}) \cdot \epsilon(\text{ID}) = \epsilon(X|\text{CT}) \cdot \epsilon(\text{ID}|\text{MS}), \quad (X = \text{Medium/Tight/High-}p_T) \quad (4.11)$$

Table 4.4 presents the selection efficiencies for various working points (WPs) [97]. As depicted in Figure 4.12a, the reconstruction efficiencies are shown as a function of p_T . For Medium muons, the efficiency is approximately 99% for $p_T > 10$ GeV and $|\eta| > 0.1$. Figure 4.12b demonstrates that the efficiency for Medium muons with $|\eta| > 0.1$ exceeds 98%, while Loose muons regain efficiency for $|\eta| < 0.1$.

Muon isolation is employed for background rejection, aiming to reduce contributions from light and heavy hadron decays within jets. Isolation is achieved by measuring detector activity around a muon candidate. Both track-based and calorimeter-based variables are utilized to quantify isolation. Figure 4.13a provides an example of such a variable. Seven isolation selection criteria have been optimized for different physics analyses. The efficiency of the FixedCutLoose selection, as a function of p_T , is illustrated in Figure 4.13b, demonstrating overall good agreement between data and simulation.

Table. 4.4: Selection efficiencies for different muon selection working points [32].

Selection	$4 < p_T < 20 \text{ GeV}$		$20 < p_T < 100 \text{ GeV}$	
	$\epsilon_\mu^{\text{MC}}[\%]$	$\epsilon_{\text{Hadrons}}^{\text{MC}}[\%]$	$\epsilon_\mu^{\text{MC}}[\%]$	$\epsilon_{\text{Hadrons}}^{\text{MC}}[\%]$
Loose	96.7	0.53	98.1	0.76
Medium	95.5	0.38	96.1	0.17
Tight	89.9	0.19	91.8	0.11
High- p_T	78.1	0.26	80.4	0.13

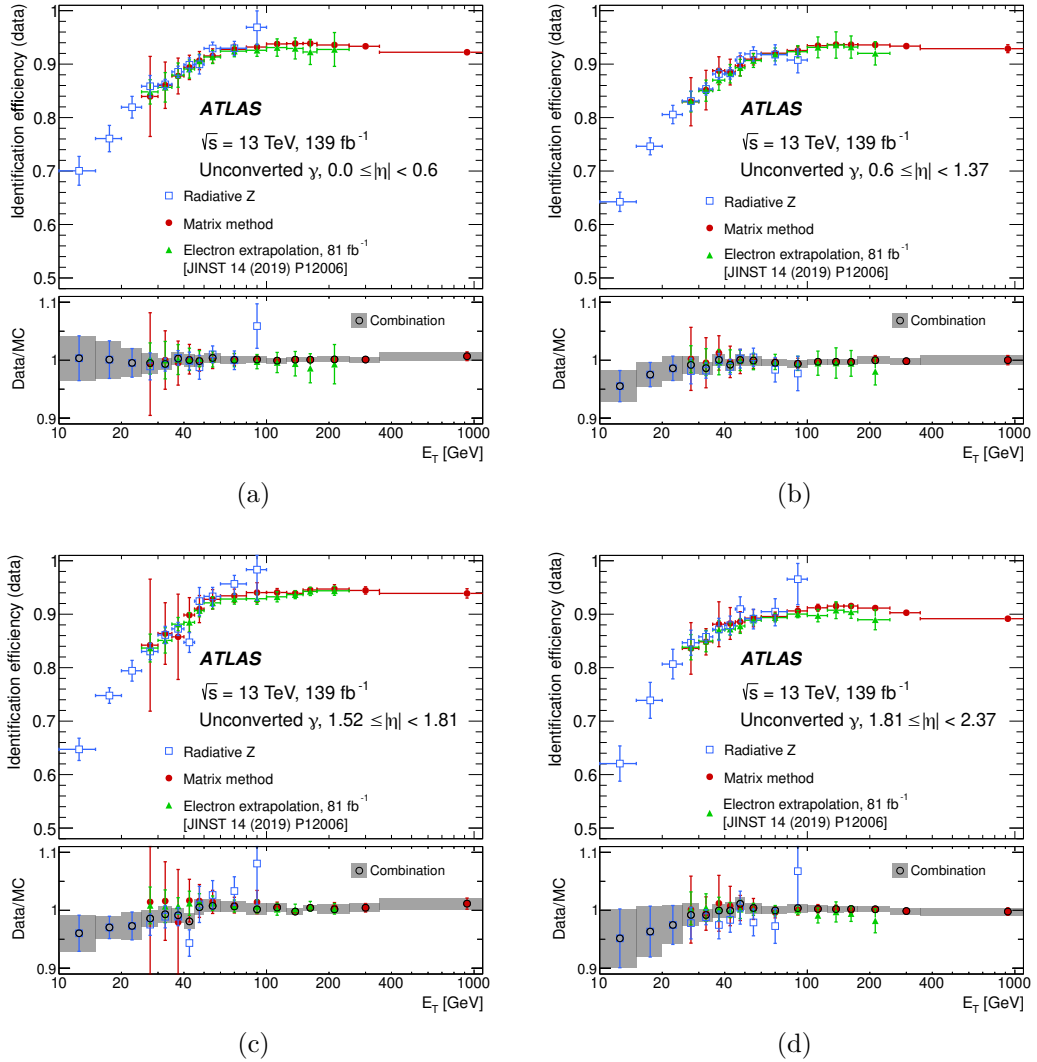


Fig. 4.8: The photon identification efficiency measured in data, along with the data-to-MC simulation efficiency ratio, is shown for unconverted photons with a Loose isolation requirement used as preselection, plotted as a function of E_T across four distinct $|\eta|$ regions. The electron extrapolation results remain unchanged from Ref. [20]. Additionally, the combined correction factor, determined by a weighted average of correction factors from individual measurements, is provided, with the band representing the total uncertainty.

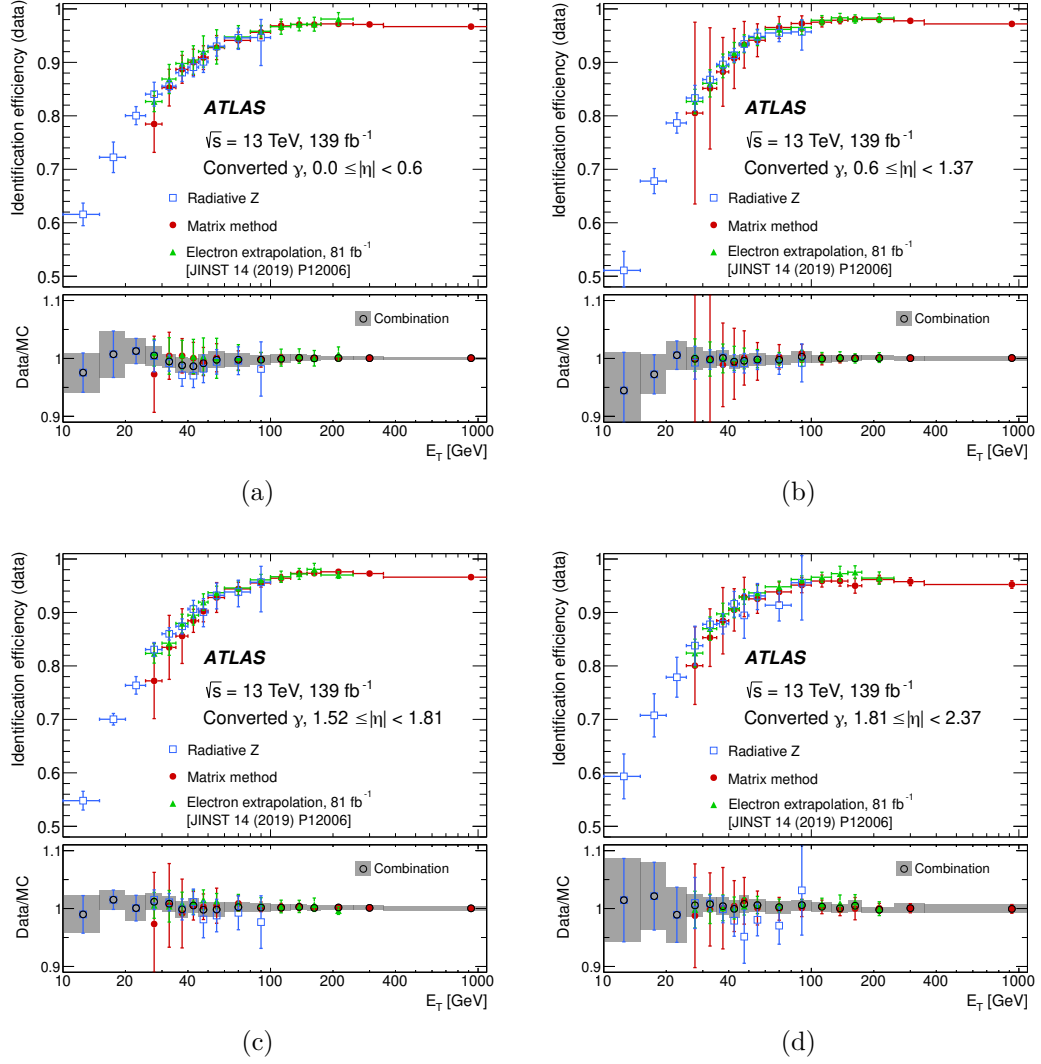


Fig. 4.9: The photon identification efficiency measured in data, along with the ratio of data to MC simulation efficiencies, is shown for converted photons with a Loose isolation requirement as preselection, plotted as a function of E_T across four different $|\eta|$ regions. The electron extrapolation results have not been updated since Ref. [20]. Additionally, the combined scale factor, derived from a weighted average of individual scale factors, is presented, with the band indicating the total uncertainty.

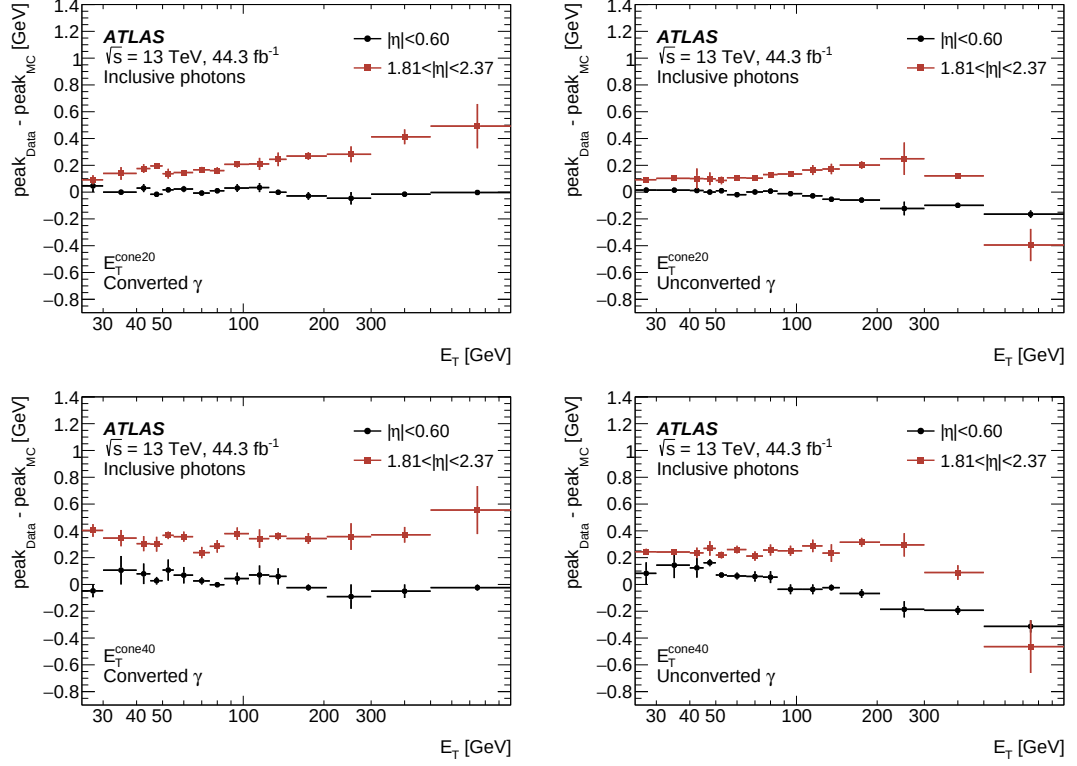


Fig. 4.10: The data-driven shifts for $E_T^{\text{cone}20}$ (top) and $E_T^{\text{cone}40}$ (bottom), derived from 2017 data and Pythia8 MC simulations, with the Tight isolation working point used as preselection to reduce background contamination. The results are presented as a function of photon E_T across two η regions of the detector ($|\eta| < 0.6$ and $1.81 < |\eta| < 2.37$), separately for converted (left) and unconverted (right) photons. Only the uncertainties related to the fit parameters are displayed.

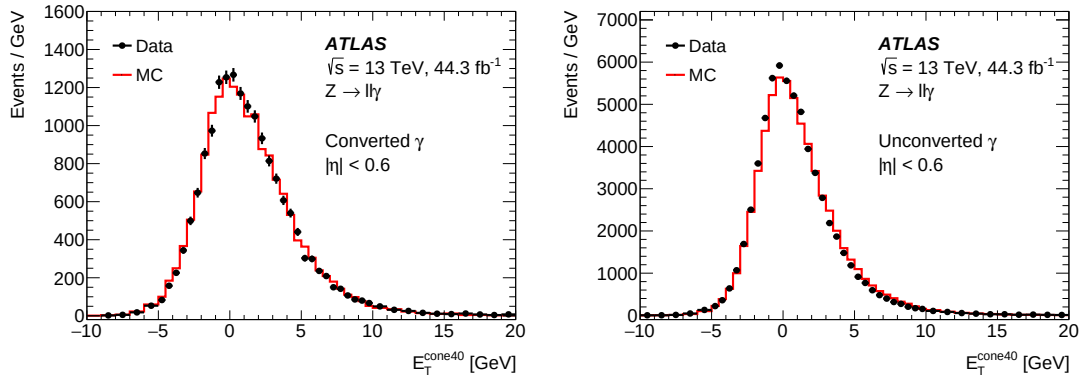


Fig. 4.11: The distribution of $E_T^{\text{cone}40}$ in both data and simulation for $Z \rightarrow \ell\ell\gamma$ events in the central detector region ($|\eta| < 0.6$), displayed separately for converted (left) and unconverted (right) photons after applying the data-driven shifts. Only statistical uncertainties are included.

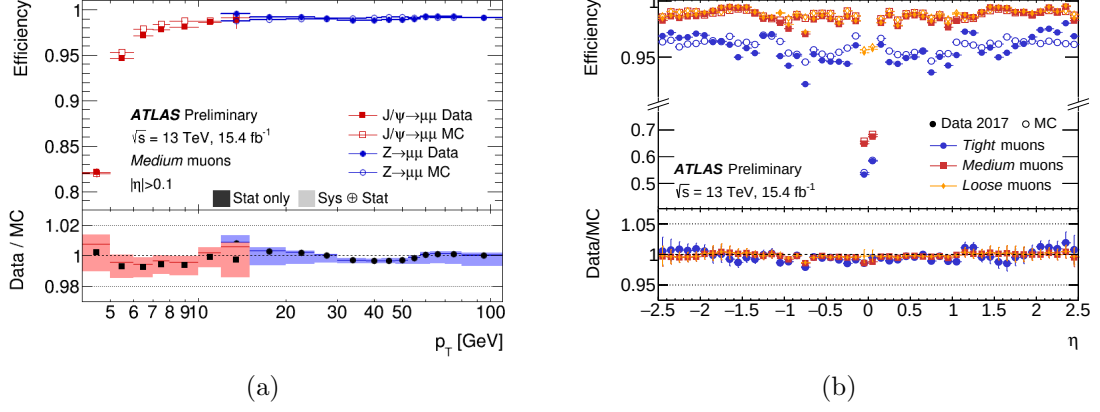


Fig. 4.12: Reconstruction efficiency plotted as a function of p_T (4.12a) and η (4.12b) [21].

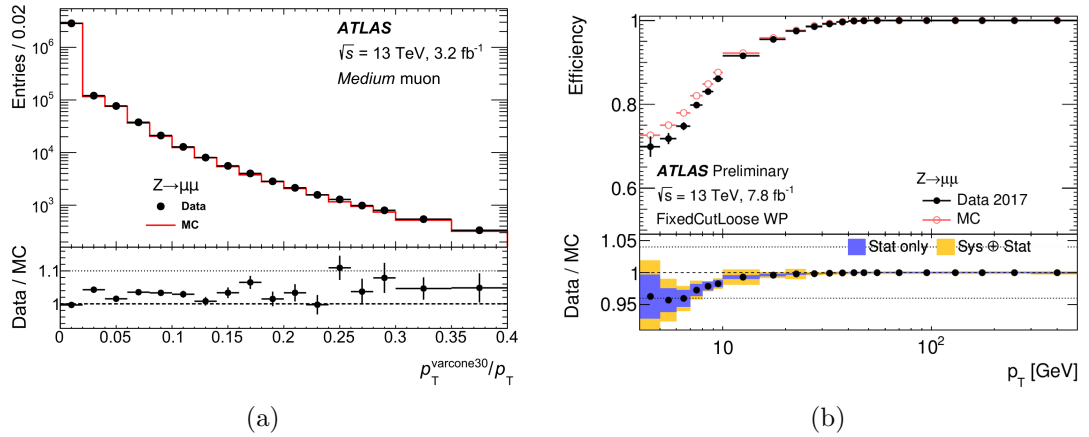


Fig. 4.13: Track-based isolation variable utilized for muon isolation (4.13a), along with isolation efficiency as a function of p_T for the FixedCutLoose isolation working point (4.13b). Figures adapted from [22] and [21].

CHAPTER 5

Data and MC simulation

5.1 ATLAS Data Taking and Luminosity

The ATLAS Data Acquisition (DAQ) system was originally designed to meet the operational requirements of the LHC’s Run 1 phase (2009–2013). In preparation for Run 2 (2015–2019), however, substantial upgrades became essential, driven by the significant enhancements implemented at the LHC during the Long Shutdown period (2013–2015). These adjustments were imperative to manage the increased demands arising from higher luminosity levels and greater event pileup characteristic of Run 2 conditions. Table 5.1 provides a summary of the principal LHC parameter changes from Run 1 to Run 2, illustrating notable increases in both peak luminosity and event pileup.

Table. 5.1: Comparison of the LHC operating conditions between Run 1 and Run 2 (as of September 2017).

Parameter	Run 1	Run 2
Center-of-mass energy	8 TeV	13 TeV
Peak luminosity	$7 \times 10^{33} \text{cm}^{-2} \text{s}^{-1}$	$1.74 \times 10^{34} \text{cm}^{-2} \text{s}^{-1}$
Average event pileup	20.7	32.2
Peak event pileup	40	60
Proton bunch crossing rate	20 MHz	40 MHz

The elevated pileup levels encountered in Run 2 created a more densely populated hit environment within the detector, increasing the challenge of distinguishing between signal and background events. This development necessitated upgrades to the DAQ system to handle the augmented data volume while preserving the precision essential for accurate physics analyses. Accordingly, significant improvements were made to the networking, storage, and computational frameworks, enabling the DAQ system to fulfill the stringent demands of Run 2 with consistent performance and operational efficiency.

The DAQ system functions by initially receiving event data from the Level-1 (L1) trigger, which reduces the initial 40 MHz event rate down to a maximum of 100 kHz. The L1 trigger utilizes custom-designed hardware to reach a decision within a $2.5 \mu\text{s}$ timeframe, filtering only the most pertinent events for subsequent processing. These selected events are then stored temporarily by the Read-Out Drivers (RODs) before being transmitted to the High-Level Trigger (HLT) system, where an advanced software-based selection process is applied, further reducing the event rate to approximately 1 kHz.

HLT processing is carried out across a computing farm of approximately 2,000 nodes, collectively hosting up to 40,000 CPU cores, allowing for high-efficiency data handling at a rate of 160 GB/s. Accepted events are then temporarily buffered within the Sub-Farm Output (SFO) system before being permanently archived in CERN's data storage infrastructure, ensuring retention of only the most relevant events for further offline analysis.

Figure 5.1 presents a schematic of the data flow within the ATLAS DAQ system during Run 2, detailing each stage from the L1 trigger through to final data storage. This figure highlights the system's enhanced capability to manage the substantially increased data rates associated with the elevated luminosity and pileup conditions characteristic of Run 2.

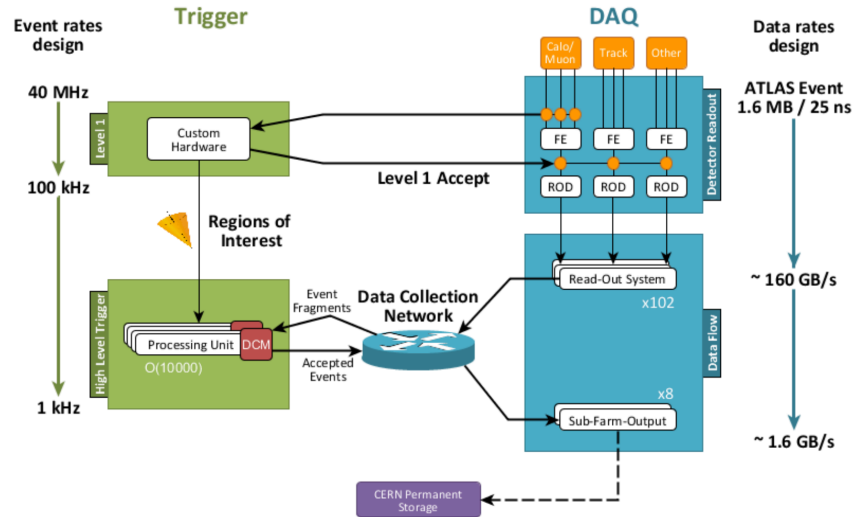


Fig. 5.1: Diagram of the ATLAS Trigger and DAQ systems in Run 2, showing the data flow from the Level-1 trigger to the High-Level Trigger, followed by the processing and storage of accepted events.

The flexibility of the DAQ system, coupled with the extensive upgrades implemented for Run 2, has been crucial in sustaining ATLAS's ability to achieve its scientific goals under the demanding conditions introduced by elevated luminosity and pileup. As the LHC progresses towards Run 3, additional advancements in

the DAQ system will be necessary to accommodate the anticipated rise in event rates and to further the search for new physics at unparalleled energy scales.

The ATLAS detector [45, 110, 111] comprises an inner tracking system enclosed by a thin superconducting solenoid that produces a 2 T axial magnetic field. This system is augmented by electromagnetic and hadronic calorimeters, along with an external muon spectrometer containing three large toroidal magnet structures. Accurate luminosity measurements within ATLAS are achieved through the use of multiple redundant detectors and algorithms, each with complementary features to minimize various sources of systematic uncertainty.

Throughout LHC Run 2, the LUCID2 Cherenkov detector [112], situated in the forward region, served as the primary instrument for determining bunch-by-bunch luminosity. This upgraded version, an improvement over the Run 1 design, delivered enhanced accuracy and reliability under the elevated luminosity conditions of Run 2.

This system was further complemented by the Beam Conditions Monitor (BCM) diamond detectors, which performed bunch-by-bunch luminosity measurements by detecting reconstructed charged particles within randomly sampled bunch crossings, a method known as track counting. In addition, the ATLAS calorimeters measured integrated luminosity by summing signals across all bunches. These signals, proportional to the instantaneous luminosity, were derived from various calorimetric quantities, including the liquid-argon (LAr) gap currents in the endcap electromagnetic (EMEC) and forward calorimeters (FCal), as well as photomultiplier currents in the Tile calorimeter (TileCal).

Figure 5.2 presents the delivered luminosity over time for 2011–2018 (proton-proton data only). In Figure 5.3, delivered luminosity represents the integrated luminosity from the beginning of stable beams until the LHC instructs ATLAS to place the detector in a safe standby mode for a beam dump or beam studies. Recorded luminosity accounts for DAQ inefficiency, as well as inefficiencies associated with the so-called “warm start”, which occurs when the stable beam flag is raised, initiating a high-voltage ramp-up in the tracking detectors and the activation of preamplifiers in the pixel system. The data quality evaluation shown corresponds to the “All Good” efficiency listed in the 2015–2018 Full Dataset DQ tables. The “All Good” Data Quality criteria require that all reconstructed physics objects meet high-quality standards.

Figure 5.4 presents the distribution of the number of interactions per bunch crossing. The average number of interactions per crossing corresponds to the mean of the Poisson distribution for interactions per crossing, calculated for each bunch. This value is derived from the instantaneous luminosity per bunch as $\mu = L_{bunch} \times \sigma_{inel}/f_r$, where L_{bunch} represents the per-bunch instantaneous luminosity,

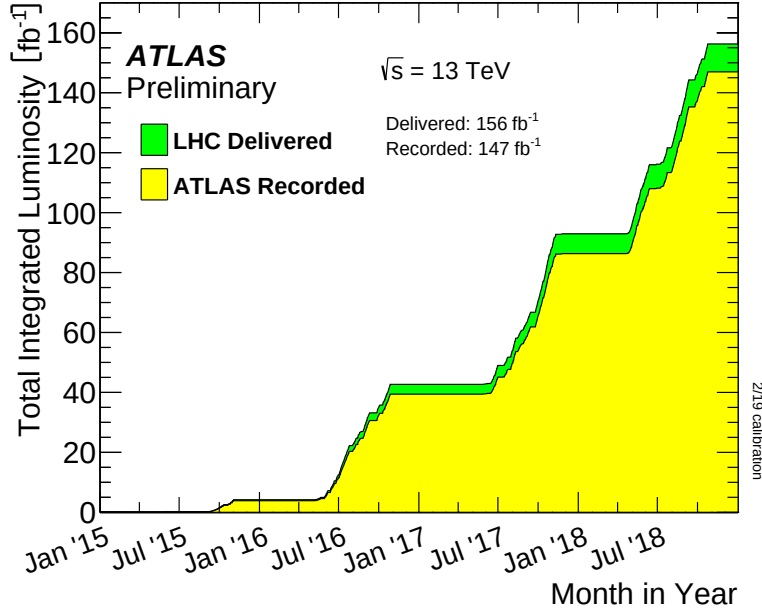


Fig. 5.2: Cumulative luminosity as a function of time provided to ATLAS during periods of stable beams and high-energy proton-proton collisions [23].

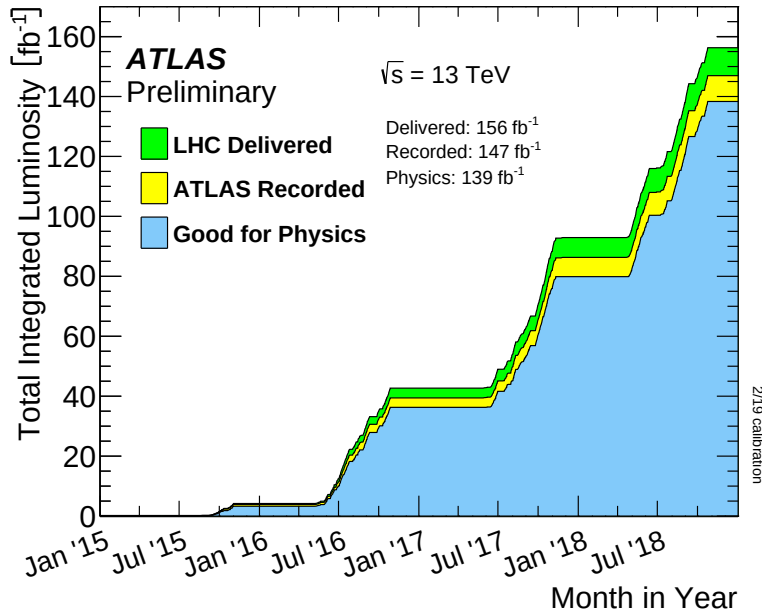


Fig. 5.3: Cumulative luminosity over time delivered to ATLAS (green), recorded by ATLAS (yellow), and validated as high-quality data (blue) during stable beam conditions for 13 TeV proton-proton collisions from 2015 to 2018. The complete 2018 proton-proton dataset is included [23].

σ_{inel} denotes the inelastic cross-section, taken as 80 mb for 13 TeV collisions, and f_r is the LHC revolution frequency.

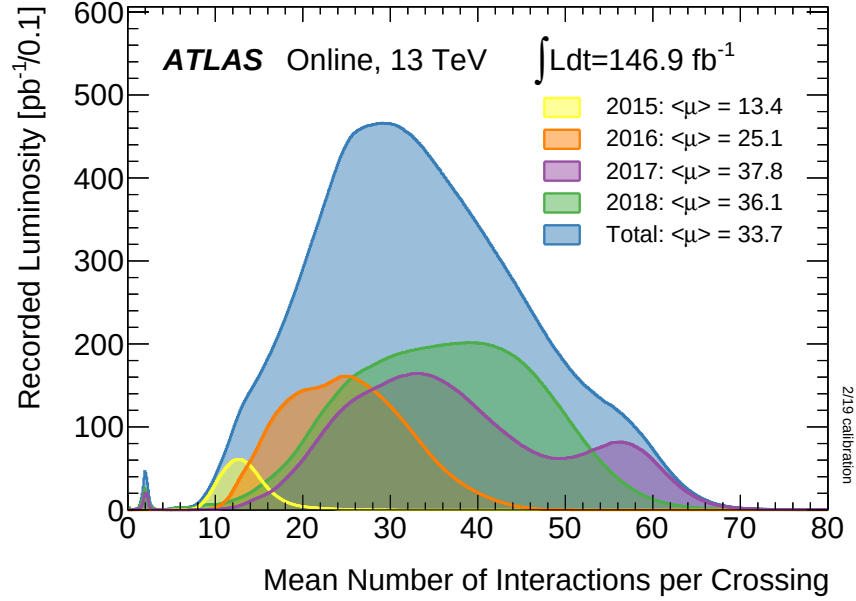


Fig. 5.4: The luminosity-weighted distribution of the mean number of interactions per bunch crossing for 13 TeV proton-proton collision data collected from 2015 to 2018. The plot encompasses all data recorded by ATLAS under stable beam conditions, with the integrated luminosity and average μ value annotated in the figure [23].

5.2 Atlas simulation

An overview of the ATLAS simulation data flow [113] is provided in Figure 5.5. Events are generated in the standard HepMC format [114]. During the event generation, filters can be applied to retain only events with specific characteristics, such as leptonic decays or missing energy above a set threshold. The generator processes prompt decays (e.g., Z or W bosons) but retains any “stable” particles that are expected to traverse parts of the detector. Since only immediate decays are considered, detector geometry does not need to be accounted for at this stage, apart from defining which particles are labeled as stable. At this step, the simulated dataset’s run number and individual event numbers are also assigned.

The generated events are subsequently read into the simulation phase. All particles produced by the generator are stored in the simulation output file, although cuts can be applied to selectively process specific particles during simulation. Each particle is propagated throughout the entire ATLAS detector using GEANT4. The detector configuration, including potential misalignments and distortions, can be customized by the user at runtime. Energy deposits in the detector’s sensitive regions are recorded as “hits”, capturing total energy deposition, position, and timing, and these are written to a simulation output file known as a hit file. For both event generation and detector simulation, information referred

5.2.1 Event generators

Event generation entails producing a set of particles that are subsequently processed through either full or fast detector simulations. This process is integrated within the Athena framework, though the event generators themselves are primarily developed and maintained by contributors outside the ATLAS collaboration. Detailed information about the framework, along with specific comments on each generator, is provided below.

Large-scale productions have utilized multiple generators, including Pythia [117] and its ATLAS-specific variant PythiaB [118, 119], HERWIG [120, 121, 122], Sherpa [123], Hijing [124], Alpgen [125], MC@NLO [126], and AcerMC [127]. Additionally, Tauola [128] and Photos [129] are routinely employed for tau decays and photon emissions, respectively, while EvtGen [130] is specifically used for B-decays in scenarios requiring detailed decay modeling.

For supersymmetric particle generation, ISAJET [131] is utilized in combination with HERWIG. Newer C++ generators, such as Pythia8 [132] and HERWIG++ [133], are currently undergoing testing. These generators produce events directly in HepMC format, eliminating the need for translation prior to simulation. As these generators are further developed, tested, and validated, they are expected to replace their FORTRAN-based predecessors. Additional productions have also employed MadGraph [134] for vector boson scattering, CHARYBDIS [135] for black hole event generation, and CompHep [136, 137] for specialized exotic physics models.

5.2.2 ATLAS detector description

The ATLAS detector is comprehensively detailed in Ref. [45]. A cut-away schematic illustrating the entire detector is shown in Figure 3.2. ATLAS consists of several concentric components, with the key subdetectors as follows:

- Beam Conditions Monitor (BCM) and Beam Loss Monitor: These systems detect hazardous conditions and can trigger a shutdown of the detector system. The BCM is positioned 1.84 meters from the interaction point (IP) at approximately $|\eta| \sim 4.2$.
- Tracking Detector: This comprises a fine granularity pixel detector with three layers covering $|\eta| < 2.5$, a silicon strip tracker (SCT) providing four space points across eight layers within $|\eta| < 2.5$, and a transition radiation tracker (TRT) that delivers 32 space points per typical track, covering $|\eta| < 2.0$.
- Hermetic Calorimetry: This system includes a liquid argon (LAr) elec-

tromagnetic calorimeter covering $|\eta| < 3.2$, a scintillating tile hadronic calorimeter in the barrel region ($|\eta| < 1.7$), a sampling LAr hadronic calorimeter in the endcap ($1.5 < |\eta| < 3.2$), and LAr electromagnetic and hadronic calorimetry in the forward region, covering $3.2 < |\eta| < 4.9$.

- Muon Chambers: Four types of muon chambers are employed, two providing high precision (monitored drift tubes and cathode strip chambers) and two offering fast response for the muon trigger (thin gap chambers and resistive plate chambers), covering $|\eta| < 2.7$.
- Luminosity Detectors: These include a zero-degree calorimeter positioned 140 meters from the interaction point, a Cherenkov-based luminosity monitor (LUCID), and an absolute luminosity detector for ATLAS.

The ATLAS magnetic field is generated by a solenoid, providing a uniform 2.0 T magnetic field in the tracking subdetectors, and a toroidal magnet system, composed of a barrel and two endcap toroid magnets. In the inner detector, the field has small ϕ - and z -asymmetries due to the toroid field and perturbations from nearby iron. The field in the toroidal system has approximate z - and eight-fold ϕ -symmetry and provides, on average, 2.5 Tm of bending power in the barrel and 5 Tm in the endcap.

5.2.3 Core simulation

The standard simulation for ATLAS relies on the Geant4 particle simulation toolkit. Geant4 provides the necessary physics models and infrastructure for particle transport through complex geometries, though several ATLAS-specific components are incorporated as custom user-code. The detector geometry is built in the Geant4 format, with all particle scoring (conducted in “sensitive detector” classes) managed on the Athena side. While initialization in a standard Athena job typically occurs in a single step, initialization for an ATLAS simulation job is divided into three stages to permit additional user input. Table 5.2 outlines the processes associated with each of these three stages.

The Geant4 simulation adds further details to the record established during event generation. Given the high volume of secondary tracks produced in detector simulations, it is infeasible to retain information for every interaction. Only interactions of significant relevance to physics analyses are preserved, based on specific storage rules (“strategies”). Most of these strategies are applied solely to the inner detector. For interactions that satisfy any of the storage criteria, details such as the incoming particle, step information, vertex, and outgoing particles are included in the truth record. Later in the software chain, individual track segments are merged, so that, for example, a single electron undergoing multiple

Table. 5.2: The initialization sequence for ATLAS simulation is segmented into multiple distinct steps, enabling user intervention at critical stages throughout the process.

Init. stage	Processes
1	External modules loaded, job properties locked, metadata written, event generation configured, hit file initialized, Geant4 service created
2	Detector, physics regions, range cuts created, GeoModel geometry translated, truth strategies initialized, magnetic field loaded, physics list selected, user actions initialized
3	Fast simulation models assigned, physics regions constructed, sensitive detectors assigned, Geant4 run manager and physics models initialized, recording envelopes and visualization initialized

bremsstrahlung events along its trajectory is recorded as one “true” particle.

The strategies include (with all kinetic energy thresholds as specified):

- In the inner detector, bremsstrahlung vertices are stored if the primary electron or muon has energy exceeding 500 MeV and the resulting photon energy is above 100 MeV.
- In the inner detector, ionization vertices are recorded if the primary particle’s energy exceeds 500 MeV and the secondary electron’s energy is above 100 MeV.
- In the inner detector, hadronic interaction vertices are retained if the primary particle has an energy above 500 MeV.
- In the inner detector, decay vertices are recorded if the decaying particle’s energy is above 500 MeV.
- In the inner detector, photon conversions with energies exceeding 500 MeV are stored.
- In the calorimeter, muon bremsstrahlung vertices are recorded if the primary muon has energy above 1 GeV and the photon produced has energy above 500 MeV.

Physics lists in Geant4 contain the numerical models that characterize particle interactions. These models are typically optimized for specific interaction types and energy ranges. The Geant4 collaboration offers several standardized physics lists, combining these models for various scenarios within each distribution. To ensure reproducibility and the application of validated model combinations, ATLAS simulations exclusively utilize physics lists provided by the Geant4 collaboration.

5.2.4 Digitization

The ATLAS digitization software translates hits from the core simulation into detector responses termed “digits”. Typically, a digit is generated when the voltage or current on a particular readout channel surpasses a preset threshold within a defined time window. For some subdetectors, digit formats include detailed signal shapes over time, while others merely register that the threshold was exceeded within the relevant time interval.

Each subdetector’s specific characteristics, such as charge collection peculiarities, cross-talk, electronic noise, and channel-dependent response variations, are modeled in subdetector-specific digitization software [138, 139, 140, 141, 142]. A top-level PYTHON digitization package manages these various subdetector digitization modules, ensuring consistency and uniformity across configurations. The properties of the digitization algorithms are tuned to replicate the detector response observed in laboratory tests, test beam data, and cosmic ray runs. Dead channels and noise rates are retrieved from database tables to accurately reproduce conditions specific to each run.

Options for digitization include:

- **Detector Noise Simulation:** Noise simulation can be disabled for the inner detector, calorimeter, muon spectrometer, or any combination thereof.
- **Random Number Services:** The type of random number engine utilized in digitization algorithms can be specified, with Ranlux64 as the default, or Ranecu [143].
- **Metadata:** By default, metadata from the simulation stage is used to configure the physics list (for setting the calorimeter sampling fraction) and the detector layout. This metadata can be overridden if needed.
- **Pile-up Background Events:** The overlay of minimum bias, cavern background, beam gas, and beam halo events can be configured independently.
- **Beam Properties:** The LHC beam bunch spacing and the number of bunch crossings to overlay before and after the hard scattering event can be specified.
- **Detector Conditions:** Default detector conditions, including dead electronics and noisy channels, are linked to each detector layout.

Digitization algorithms are implemented for the following subdetectors:

- **Inner Detector:** BCM, silicon pixel tracker, SCT, and TRT.®
- **Calorimeter:** LAr and tile calorimeters. Separate algorithms exist to simulate the formation of trigger towers in the calorimeters, serving as inputs to

the level one trigger.

- Muon Spectrometer: Cathode Strip Chambers, Monitored Drift Tubes, Resistive Plate Chambers, and Thin Gap Chambers.

If requested, the level one trigger simulators are added to the algorithm sequence, provided that digitization for the relevant ATLAS components has been enabled. The default mode for simulation production is to execute the level one trigger simulation during the reconstruction phase, rather than as part of the digitization step.

5.2.5 Fast Simulation

Given the intricate detector geometry and detailed physics modeling utilized in the ATLAS Geant4 simulation, obtaining the required statistics for many physics analyses would be impractical without a faster simulation method. To address this, several fast simulation tools have been developed to complement the Geant4 simulation. In this context, the standard Geant4 simulation is referred to as “full simulation”.

Approximately 80% of the full simulation time is allocated to simulating particles traversing the calorimeters, with around 7% dedicated to electromagnetic particles. The Fast Geant4 Simulation is designed to accelerate this most time-intensive part of the full simulation [144, 145]. This approach involves discarding low-energy electromagnetic particles within the calorimeter and substituting them with pre-simulated showers stored in memory. Utilizing this technique reduces CPU time by a factor of three for hard scattering events (such as $t\bar{t}$ production) with negligible effect on physics accuracy. This fast simulation method may eventually become the standard for processes not requiring highly precise modeling of calorimeter response or electromagnetic interactions.

CHAPTER 6

Observation and differential cross-section measurements of electroweak $W \rightarrow (l\nu)\gamma jj$

6.1 Introduction

Vector boson scattering (VBS), characterized by the process $VV \rightarrow VV$ with $V = W, Z, \gamma$, is a crucial probe of electroweak symmetry breaking in the Standard Model (SM) due to the involvement of both triple and quartic gauge couplings [146]. In proton-proton (pp) collisions, the $W\gamma jj$ final state can arise through various electroweak (EW) mechanisms, including processes of order α_{EW}^4 [147], where α_{EW} denotes the electroweak coupling constant. VBS diagrams involving quartic gauge couplings (QGCs) play a key role, though they cannot be isolated in a gauge-invariant manner from other EW contributions.

The dominant background arises from strong interactions at order $\alpha_s^2\alpha_{\text{EW}}^2$, where α_s is the strong coupling constant, leading to strong $W\gamma jj$ production [147]. In this analysis, we focus on electroweak $W\gamma jj$ production and measure the differential cross-section with a data set of 140 fb^{-1} from the ATLAS detector.

The CMS Collaboration previously reported the observation of EW $W\gamma jj$ production [148]. This study builds upon CMS by employing multivariate techniques to enhance signal extraction and introducing measurements sensitive to charge conjugation (C) and parity (P) symmetry, exploring potential CP-violating effects in the gauge boson sector. These measurements enhance sensitivity to anomalous QGCs, especially those involving $WW\gamma\gamma$ and $WW\gamma Z$ couplings.

The differential cross-sections are evaluated using two categories of observables. First, VBS observables—designed to capture VBS characteristics and potential anomalous QGCs—include the dijet invariant mass m_{jj} , the transverse momentum of the jets p_T^{jj} , and the lepton-photon invariant mass $m_{l\gamma}$. Second, CP-sensitive observables include the signed azimuthal angle difference between the jets, $\Delta\phi_{jj}$, and between the lepton and photon, $\Delta\phi_{l\gamma}$, providing insights into

the CP structure of the $WW\gamma\gamma$ and $WW\gamma Z$ interactions.

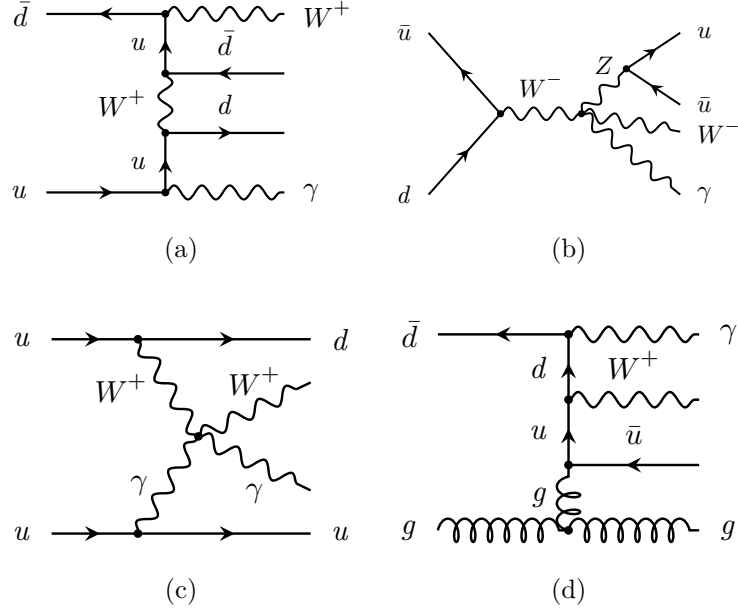


Fig. 6.1: Representative Feynman diagrams for the $W\gamma jj$ final state: (a) Electroweak (EW) $W\gamma jj$ production without gauge boson self-interactions, (b) bremsstrahlung EW $W\gamma jj$ non-VBS production involving quartic gauge boson interactions, (c) $W\gamma$ VBS involving quartic gauge boson interactions, and (d) QCD $W\gamma jj$ production.

6.2 Data and MC Samples

6.2.1 Monte Carlo

Monte Carlo (MC) samples are used to simulate signal and background events, crucial for defining analysis selections and evaluating systematic uncertainties. In some cases, they are also employed in control regions for data-driven background estimation. MC samples are generated using ATLAS Athena with the STDM4 derivation. A summary of event generators is provided in Table 6.1.

The nominal electroweak (EW) $W\gamma jj$ signal is simulated with Sherpa 2.2.12 [149] at leading order (LO) using the NNPDF3.1 PDF set [150]. Additionally, EW $W\gamma jj$ and $Z\gamma jj$ events are generated with MadGraph5 [151], also at LO. Parton-level events are passed to Pythia8 for parton-showering, hadronization, and underlying event modelling using the A14 tune [152], while EvtGen [130] handles heavy-flavor decays.

A cross-section discrepancy is observed between Sherpa (1.78 nb) and MadGraph (2.52 nb) for the EW $W\gamma jj$ signal. The Sherpa sample, due to higher precision, is used as the default, but results from both generators are reported.

Table. 6.1: A summary of the Monte Carlo event generators used for simulating events in the analysis. Additional details and references are provided in the text. Monte Carlo samples of prompt backgrounds serve as templates for the fits used in the analysis, whereas non-prompt background samples are only utilized in control regions for data-driven fake estimates or in closure tests of these estimates.

Process	Prompt/Non-prompt	Generator	ME Accuracy	PDF	Shower and Hadronization	Parameter Tune
EW $W\gamma jj$	Prompt	MadGraph5	LO	NNPDF3.1 LO	Pythia8+EvtGen	A14
		Sherpa 2.2.12	LO	NNPDF3.0 NLO	Sherpa	Default
QCD $W\gamma jj$	Prompt	Sherpa 2.2.11	LO	NNPDF3.0 NLO	Sherpa	Default
		MadGraph5	NLO	NNPDF3.0 NLO	Pythia8+EvtGen	A14
EW $Z\gamma jj$	Prompt	MadGraph5	LO	NNPDF3.1 LO	Pythia8+EvtGen	A14
QCD $Z\gamma jj$	Prompt	Sherpa 2.2.11	NLO	NNPDF3.0 NLO	Sherpa	Default
		MadGraph5	LO	NNPDF3.1 LO	Pythia8+EvtGen	A14
Single Top	Non-prompt	Sherpa 2.2.11	NLO	NNPDF3.0 NLO	Sherpa	Default
		Powheg	NLO	NNPDF3.0 NLO	Pythia8+EvtGen	A14
Z + jets	Non-prompt	Sherpa 2.2.11	NLO	NNPDF3.0 NNLO	Sherpa	Default
		Sherpa 2.2.11	NLO	NNPDF3.0 NNLO	Sherpa	Default
Diboson	Non-prompt	Sherpa 2.2.12	NLO	NNPDF3.0 NNLO	Sherpa	Default
Dijet	Non-prompt	Pythia8	LO	NNPDF2.3 LO	Pythia8+EvtGen	A14
EW $W\gamma jj$	Non-prompt	Sherpa 2.2.1	NLO	NNPDF3.0 NLO	Sherpa	Default
EW $Z\gamma jj$	Non-prompt	Sherpa 2.2.1	NLO	NNPDF3.0 NLO	Sherpa	Default
$t\bar{t}$	Non-prompt	Powheg	NLO	NNPDF3.0 NLO	Pythia8+EvtGen	A14
tW	Non-prompt	Powheg	NLO	NNPDF3.0 NLO	Pythia8+EvtGen	A14

The dominant background arises from $W\gamma jj$ production via strong interactions, simulated using Sherpa 2.2.11 at NLO for up to two partons and LO for two to four partons. The Comix [153] and OpenLoops [154, 155] libraries are used, with CKKW matching [156]. The NNPDF3.0 PDF set is employed at NLO, and Sherpa is used for parton-showering, hadronization, and underlying event simulation. This serves as the nominal QCD background estimate, with QCD $Z\gamma jj$ and W +jets samples used for closure tests.

A second QCD $W\gamma jj$ sample is generated using MadGraph5 at NLO with NNPDF3.0 and Pythia8 (A14) for parton-showering. EvtGen is used for heavy-flavor decays. Backgrounds from $tW\gamma$, $tq\gamma$, and $t\bar{t}\gamma$ are simulated using MadGraph5 at LO with Pythia8 for showering, and EvtGen for decays.

Single-top t -channel events are generated using Powheg at NLO with NNPDF3.0, and Pythia8 for showering and hadronization. The overlap between tW and $t\bar{t}$ is treated using the DR scheme [157].

Diboson and dijet events are simulated with Sherpa 2.2.2 (NLO) and Pythia8 (LO), respectively, and used for data-driven jet faking estimates. EW $W\gamma jj$ and $Z\gamma jj$ samples are used for cross-checks of the photon fake estimation.

All MC samples are processed through GEANT4 [158] for ATLAS detector simulation and are reconstructed using the same algorithms as the data. Corrections are applied on an event-by-event basis to account for differences in trigger, reconstruction, and identification efficiencies between data and MC. Pileup is simulated using Pythia8 with the A3 tune.

6.2.2 Sample Overlap Removal

To prevent double counting, samples with n photons in the matrix element are combined with $n - 1$ photon samples, where additional photons originate from the parton shower. These samples are subject to cuts on the photon transverse momentum and ΔR with the lepton. Overlap occurs when photons from the shower pass the kinematic cuts applied to dedicated photon samples. To address this, an overlap removal procedure is applied to all relevant sample pairs, such as $W\gamma$ and VBF W , EW $Z\gamma$ and VBF Z , QCD $W\gamma$ and W +jets, QCD $Z\gamma$ and Z +jets, $t\bar{t}\gamma$ and $t\bar{t}$, $tW\gamma$ and tW . The VGammaORTool [159] is used to ensure proper removal of overlapping events.

6.2.3 Data

This analysis uses the full Run 2 dataset collected by the ATLAS detector from 2015 to 2018, with proton-proton (pp) collisions at a center-of-mass energy of $\sqrt{s} = 13$ TeV provided by the LHC. Data quality criteria ensure that only runs meeting the detector’s operational standards are included. The dataset represents an integrated luminosity of 140 fb^{-1} , with a 1.7% uncertainty on the luminosity measurement [160].

6.3 Object Definitions and Event Selections

This analysis targets the measurement of $W\gamma$ VBS, where the W boson decays leptonically into an electron or muon. The final state consists of an isolated lepton, an isolated photon, two jets, and missing transverse momentum.

6.3.1 Leptons

Electrons are reconstructed using energy deposits in the calorimeter, matched with tracks in the inner detector (ID). Muons are identified by combining information from the ID and the muon spectrometer (MS). The baseline selection criteria for electrons and muons are detailed in Table 6.2 and Table 6.3, respectively.

Table. 6.3: Baseline selection criteria for muons.

Trigger requirement: HLT_mu20_loose_L1MU15 or HLT_mu26_ivarmedium or HLT_mu50
Kinematic Acceptance: $p_T > 30 \text{ GeV}$
Geometrical Acceptance: $ \eta < 2.5$
Impact parameter: $ z_0 \times \sin \theta < 0.5 \text{ mm}$ and $ d_0/\sigma_{d_0} < 3$
Identification working point: Tight
Isolation working point: PflowTight_VarRad isolation

Table. 6.2: Baseline selection criteria for electrons.

Trigger requirement: HLT_e24_lhmedium_L1EM20VH or HLT_e60_lhmedium or HLT_e120_lhloose or HLT_e26_lhtight_nod0_ivarloose or HLT_e60_lhmedium_nod0 or HLT_e140_lhloose_nod0
Kinematic Acceptance: $p_T > 30$ GeV
Geometrical Acceptance: $ \eta < 2.47$, excluding $1.37 \leq \eta \leq 1.52$
Impact parameter: $ z_0 \times \sin \theta < 0.5$ mm and $ d_0/\sigma_{d_0} < 5$
Identification working point: Tight
Isolation working point: Tight_VarRad

6.3.2 Photons

Photons are required to pass tight identification and isolation criteria [161]. The tight isolation condition is defined as $E_T^{\text{cone40}} < 0.022 \times p_T + 2.45$ GeV, where E_T^{cone40} is the scalar sum of transverse energies from topological clusters within a radius of $\Delta R = 0.4$ around the photon candidate [161]. Photons must satisfy $p_T > 22$ GeV and $|\eta| < 2.37$, excluding the calorimeter's transition region $1.37 < |\eta| < 1.52$.

6.3.3 Jets

Jets are selected with $p_T > 25$ GeV and $|\eta| < 4.4$. For jets with $p_T < 60$ GeV and $|\eta| < 2.4$, the tight working point of the jet vertex tagger (JVT) [162] is applied to ensure they originate from the primary vertex. Jets associated with noise bursts in the calorimeter are vetoed [163]. Events must contain at least two jets with $p_T > 50$ GeV. Jets within $|\eta| < 2.5$ that contain b -hadrons are tagged using a multivariate algorithm (DL1r) [164] with an 85% efficiency working point. Events with b -jets, as identified by the DL1r algorithm, are rejected to suppress top-quark backgrounds.

6.3.4 Missing transverse momentum

The magnitude of the missing transverse momentum (E_T^{miss}) is computed as the negative vector sum of the track-based soft term and the four-momenta of all reconstructed electrons, muons, photons, and jets [105]. The soft term includes tracks from the primary vertex that are not associated with hard objects. Events are required to satisfy $E_T^{\text{miss}} > 30$ GeV.

6.3.5 Event selection

An overlap removal procedure is applied to resolve reconstruction ambiguities between physics objects. Jet candidates are discarded if $\Delta R(j, l) < 0.2$ ($l = e, \mu$).

Next, leptons are rejected if $\Delta R(l, j) < 0.4$, and photons are removed if $\Delta R(\gamma, l) < 0.4$ or $\Delta R(\gamma, j) < 0.4$. Electron candidates are also excluded if they share an inner detector (ID) track with a muon.

Events must satisfy $m_T^W > 30$ GeV, where $m_T^W = \sqrt{2p_T^l E_T^{\text{miss}}(1 - \cos \Delta\phi)}$, with $\Delta\phi$ the azimuthal angle difference between the lepton and missing transverse energy. To reduce contamination from events with a lepton misidentified as a photon in $Z \rightarrow ll$ decays, the invariant mass of the lepton and photon must fulfill $|m_{l\gamma} - m_Z| > 10$ GeV. Additionally, events are rejected if a second lepton satisfying $p_T > 7$ GeV, the lepton-specific pseudorapidity requirements, track impact parameter constraints, and loose identification [165, 166] is found, to suppress contributions from $Z \rightarrow ll$ and diboson processes.

Finally, the two leading jets are required to have a rapidity separation of $|\Delta y_{jj}| > 2$ and an invariant mass $m_{jj} > 500$ GeV to ensure a topology consistent with $EW W\gamma jj$ production.

6.3.6 Signal and control regions

The selection criteria outlined above form the baseline selection. Baseline-selected events are further subdivided into signal and control regions based on the specific analysis objective. For the fiducial cross-section measurement of $EW W\gamma jj$ production, the baseline region is split into a signal region (SR^{fid}) and a control region (CR^{fid}) by counting jets within the rapidity gap between the two leading jets, $N_{\text{jets}}^{\text{gap}}$. Events with $N_{\text{jets}}^{\text{gap}} = 0$ are classified as belonging to the signal region (SR^{fid}), while events with $N_{\text{jets}}^{\text{gap}} > 0$ are categorized into the control region (CR^{fid}).

In the differential cross-section measurement, an additional requirement of $m_{jj} > 1$ TeV is applied to increase the purity of the $EW W\gamma jj$ signal. Events satisfying this criterion are then divided into three control regions (CR_A , CR_B , CR_C) and one signal region (SR). The lepton-photon system's centrality relative to the two leading VBS-tagged jets (j_1, j_2) is quantified as $\xi_{l\gamma} = |(y_{l\gamma} - \frac{y_{j_1} + y_{j_2}}{2}) / (y_{j_1} - y_{j_2})|$, where $y_{l\gamma}$ represents the rapidity of the lepton-photon system. The differential cross-section analysis uses this centrality variable to define the regions: the signal region (SR) corresponds to events with minimal hadronic activity between the two leading jets and a centrally produced $l\gamma$ system ($N_{\text{jets}}^{\text{gap}} = 0, \xi_{l\gamma} < 0.35$).

The remaining three control regions are used to constrain the dominant background from *strong* $W\gamma jj$ production. These regions are defined as follows: CR_A ($N_{\text{jets}}^{\text{gap}} > 0, \xi_{l\gamma} < 0.35$), CR_B ($N_{\text{jets}}^{\text{gap}} > 0, 0.35 < \xi_{l\gamma} < 1$), and CR_C ($N_{\text{jets}}^{\text{gap}} = 0, 0.35 < \xi_{l\gamma} < 1$). Table 6.4 summarizes the signal and control regions for both the fiducial and differential cross-section measurements.

Table. 6.4: Summary table of the signal and control regions used for fiducial and differential cross-section measurements.

Fiducial cross-section	SR ^{fid}		CR ^{fid}	
	$N_{\text{jets}}^{\text{gap}} = 0$		$N_{\text{jets}}^{\text{gap}} > 0$	
Differential cross-section	SR	CR _A	CR _B	CR _C
$m_{jj} > 1 \text{ TeV}$	$N_{\text{jets}}^{\text{gap}} = 0$ $\xi_{l\gamma} < 0.35$	$N_{\text{jets}}^{\text{gap}} > 0$ $\xi_{l\gamma} < 0.35$	$N_{\text{jets}}^{\text{gap}} > 0$ $0.35 < \xi_{l\gamma} < 1$	$N_{\text{jets}}^{\text{gap}} = 0$ $0.35 < \xi_{l\gamma} < 1$

Table 6.5 presents the event yields for signal and background processes in SR^{fid} and CR^{fid}, after applying the data-driven background estimation described in Section 6.5. The *strong* $W\gamma jj$ process dominates, contributing 63% of the total event yield in CR^{fid} and 52% in SR^{fid}. Other prompt backgrounds, including top quark processes and electroweak and strong $Z\gamma jj$ production, account for 11% in CR^{fid} and 8% in SR^{fid}. The non-prompt backgrounds contribute 22% in CR^{fid} and 23% in SR^{fid}.

Table. 6.5: The expected number of events in the signal and control regions for the fiducial cross-section measurement and observation of EW $W\gamma jj$ production. Statistical and systematic uncertainties, as estimated in Section 6.6, are included for each component. The observed number of events in each region is provided for comparison. The “non-prompt” background category accounts for non-prompt photons and fake leptons.

	SR ^{fid} ($N_{\text{jets}}^{\text{gap}} = 0$)	CR ^{fid} ($N_{\text{jets}}^{\text{gap}} > 0$)
EW $W\gamma jj$	520 ± 141	120 ± 49
Strong $W\gamma jj$	1550 ± 830	1970 ± 950
Non-prompt	692 ± 57	698 ± 58
Top quark processes	109 ± 18	183 ± 37
EW + strong $Z\gamma jj$	128 ± 34	163 ± 77
Total	3000 ± 830	3140 ± 960
Data	3341	3143

6.4 Neural Network For Signal Classification

This analysis employs multivariate analysis (MVA) techniques to enhance the sensitivity to the electroweak process under investigation. This section outlines the training and performance of a Neural Network (NN) used to distinguish between signal and background events.

6.4.1 Neural Network Architecture and Inputs

A NN is trained using the Sherpa signal sample and all prompt background Monte Carlo (MC) samples, including QCD $W\gamma jj$, $Z\gamma jj$, and top-quark backgrounds, implemented via TensorFlow [167] and Keras [168]. The training dataset is derived from events passing the signal region selection criteria: $m_{jj} > 500$ GeV, $\Delta Y(jj) > 2$, and the absence of additional jets in the rapidity gap between the two leading transverse momentum jets. This defines a signal-enriched region for training the NN, while a control region enriched in QCD background is defined by events with more than one jet in the rapidity gap. Training on the number of rapidity gap jets resulted in the NN heavily favoring this feature, so the jet cut is applied to ensure the network exploits other kinematic features more effectively.

To fully utilize the available MC statistics, two neural networks are trained: one using events with odd event numbers and the other with even event numbers. The complementary set of events is used for evaluation and validation. The NN output score in data is taken as the average of the outputs from the two networks. During training, binary cross-entropy is used as the loss function, with each event's loss weighted by its normalized event weight. Furthermore, the total background cross-section in the training region is normalized to match that of the signal.

The NN is trained to classify signal and background using a set of 13 kinematic variables, as detailed below.

- $\xi_{l\gamma}$ • $pT_{l\gamma}$ • $|\Delta\phi(l\gamma, jj)|$ • $\Delta R(l, \gamma)$
- pT_{γ} • η_{j_0} • $\Delta R(l\gamma, jj)$
- pT_l • M_W^T • $\Delta R(\gamma, j_0)$
- pT_{j_0} • $|\Delta\eta(j_0, j_1)|$ • ξ_{γ}

The normalized distributions of the input variables for both signal and background events within the training region are shown in Figure A.1 in Appendix A.1. The linear correlation coefficients between these variables for both signal and background are displayed in Figure 6.2.

Table. 6.6: Summary of the hyper-parameter search. Optimal values are highlighted in bold.

Hyper-parameter	Values
Number of hidden layers	2,3,4,5,7
Nodes per layer	64,128,256,512,1024
Learning rate	1e-5,3e-5,1e-4,3e-4,1e-3

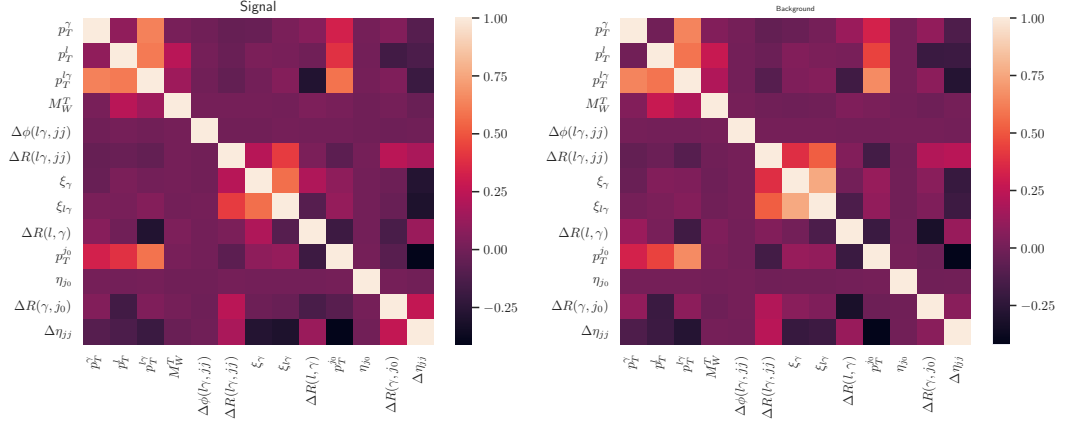


Fig. 6.2: Linear correlation coefficients for training variables within Monte Carlo signal and background samples.

The neural network architecture comprises an initial batch normalization layer followed by three fully connected hidden layers, each consisting of 512 nodes. Each hidden node utilizes the LeakyReLU activation function, which is mathematically expressed in Equation 6.1. The output layer is densely connected to the final hidden layer and employs a sigmoid activation function, as defined in Equation 6.2. The model is trained using the Adam optimizer [169], with an initial learning rate of 3×10^{-5} . The architecture of the network, including the number of hidden layers, nodes, and the learning rate, was optimized through a grid search. This approach involves iteratively training the model with different combinations of hidden layers, node counts, and learning rates, selecting the architecture that minimizes the loss on test data. A summary of the grid search procedure is provided in Table 6.6.

$$f(x) = \begin{cases} 0.01x, & \text{if } x < 0 \\ x, & \text{otherwise} \end{cases} \quad (6.1)$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (6.2)$$

6.4.2 Neural Network Training

The neural network trained on Monte Carlo events with even event numbers exhibits a larger generalization gap (i.e., the difference between training and validation loss) compared to the network trained on odd event numbers. However, the reduction in training loss for the even-numbered network does not result in an increase in validation loss, indicating no degradation in generalization. Additionally, both networks demonstrate similar performance and do not exhibit overfitting. This is evident from Figure 6.3, which shows that the output distributions for signal and background are consistent between the training and validation datasets for both the even and odd event-numbered networks.

The neural network performance is quantified using the area under the receiver operating characteristic (ROC) curve (AUC), which measures the true positive rate as a function of the false positive rate. The ROC curves for both networks are shown in Figure 6.4. Both networks achieve an AUC of 0.75, demonstrating equivalent classification performance.

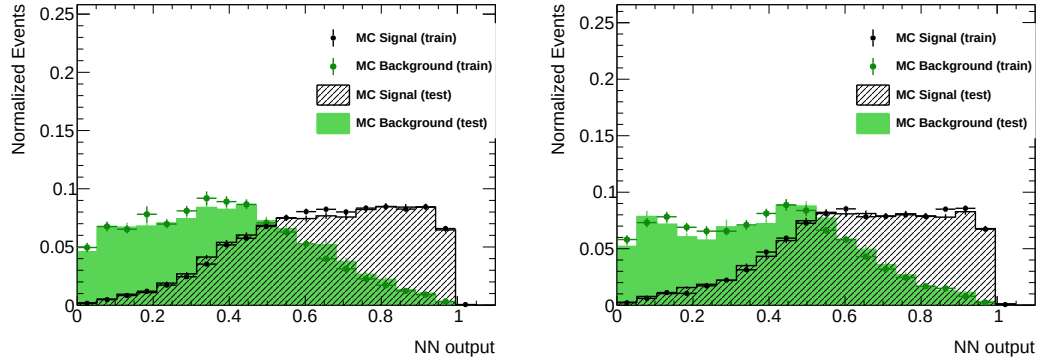


Fig. 6.3: Signal and background shapes for training and validation samples of the neural network, trained on even event number MC (left) and odd event number MC (right).

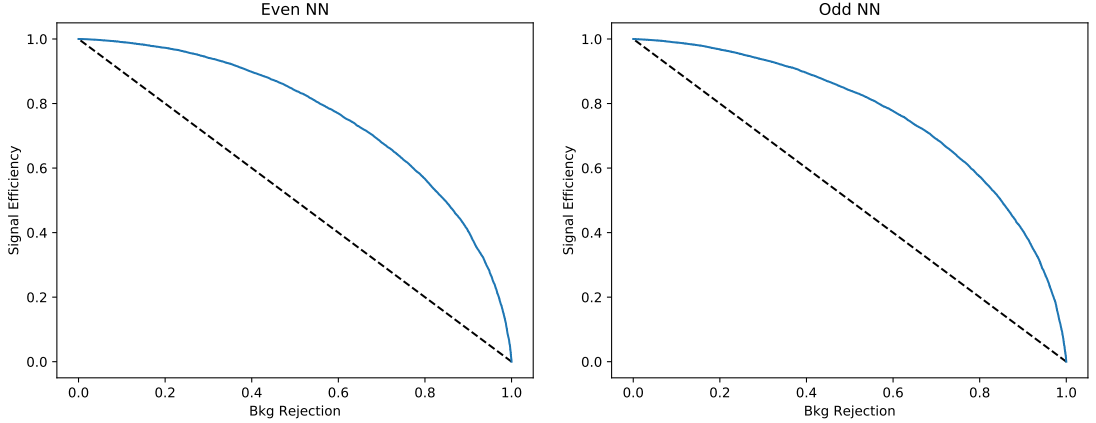


Fig. 6.4: Receiver operating characteristic (ROC) curves for the neural network trained on even event number MC (left) and odd event number MC (right).

6.5 Background estimation

The dominant background originates from strong $W\gamma jj$ production, which is modeled through MC simulation and further constrained by data in control regions. Additional prompt backgrounds stem from $Z\gamma jj$ production and top-quark production in association with photons. The primary non-prompt background is due to $W + \text{jets}$ events, where a jet is misidentified as a photon. This background is estimated using a data-driven template fit. A “fake factor” method is employed to estimate backgrounds from fake leptons, which arise from mis-reconstructed jets or hadron decays in flight.

Electrons can also be misidentified as converted photons ($e \rightarrow \gamma$) if the track reconstruction fails to associate the correct B-layer hit or incorrectly assigns a conversion track to the electron. Moreover, pile-up backgrounds can arise from selecting a photon from one pp interaction and a Wjj event from another. This pile-up photon background is estimated using a data-driven approach [170], which leverages the difference in Δz_γ between hard scatter and pile-up photons.

6.5.1 Jet faking photons

Due to the inadequate modelling of jet showering in the calorimeter, a data-driven method is employed to estimate this background instead of relying on Monte Carlo simulation. A template fit method is utilized to extract the distribution of jets misidentified as photons.

6.5.1.1 The template fit method

The template fit method leverages the difference in the isolation energy distribution between tight and non-tight photon candidates, where the isolation energy

is defined as

$$E_{iso} = E_T^{cone40} - 0.022 * pT. \quad (6.3)$$

To determine the number of jets mimicking tight and isolated photons, the method is conducted as follows in each bin:

- The shape of the prompt photon template is extracted by fitting the isolation distribution of tight, truth-matched photons from Monte Carlo. The Sherpa electroweak $W\gamma jj$ and Sherpa QCD $W\gamma jj$ samples with real photons are used to define this template due to their rich statistics.
- The jet-faking-photon template is derived by fitting the isolation distribution of non-tight data events.
- A probability density function (PDF) is constructed by summing the prompt photon and jet-faking photon templates. The normalization is then fit to data containing reconstructed tight photons. The template shape parameters are allowed to float but are constrained by multivariate Gaussians based on the best-fit parameters and their uncertainties from the template extraction. This approach ensures the statistical uncertainties from the fit are propagated to the final result.
- The jet-faking-photon component is integrated up to the 2.45 GeV threshold for photon isolation to estimate the yield of tight and isolated jet-faking photons.

For each template, various functional forms were tested. The double-sided Crystal Ball function was found to provide the best fit for the prompt photon template, while a Novosibirsk function was used for the jet-faking photon template. The Crystal Ball function, defined below, is a Gaussian with a power-law tail:

$$f_{CB} = \begin{cases} \exp(-\frac{(E-E_0)^2}{2\sigma^2}) & \frac{E-E_0}{\sigma} > -\alpha \\ (\frac{n}{|\alpha|})^n \exp(-\frac{|\alpha|^2}{2})(\frac{n}{|\alpha|} - |\alpha| - \frac{E-E_0}{\sigma})^{-n} & \frac{E-E_0}{\sigma} \leq -\alpha \end{cases} \quad (6.4)$$

where E_0 is the Gaussian mean, σ is its width, α is the cutoff parameter, and n defines the power-law tail. The double-sided Crystal Ball function is constructed by combining two Crystal Ball functions with a shared mean and width.

The Novosibirsk probability density function (PDF) is given by

$$f_N = e^{-\frac{1}{2}\left(\frac{\ln^2(q_y)}{\Lambda^2} + \Lambda^2\right)} \quad (6.5)$$

where

$$q_y = 1 + \frac{\Lambda(x - x_0)}{\sigma} \times \frac{\sinh\left(\Lambda\sqrt{\ln 4}\right)}{\Lambda\sqrt{\ln 4}} \quad (6.6)$$

with x_0 representing the peak position, σ the peak width, and Λ controlling the tail behavior of the distribution. In the following sections, $f_T(x|\theta_T)$ refers to the double-sided Crystal Ball PDF for tight photons, while $f_{NT}(x|\theta_{NT})$ denotes the Novosibirsk PDF for non-tight photons. Here, x represents the photon isolation, and θ are the free parameters of the fit.

6.5.1.2 Tight fit

The prompt photon template is extracted by performing an unbinned fit of the isolation distribution for tight, truth-matched photons from Monte Carlo using the double-sided Crystal Ball function. The fit minimizes the negative log-likelihood, given by:

$$-\ln \mathcal{L} = -\ln \prod_i f_T(x|\theta_T) \quad (6.7)$$

where i runs over all events. The tight photon templates are shown in five bins of the neural network score within the control region, defined by the presence of jets in the rapidity gap, in Figure 6.5.

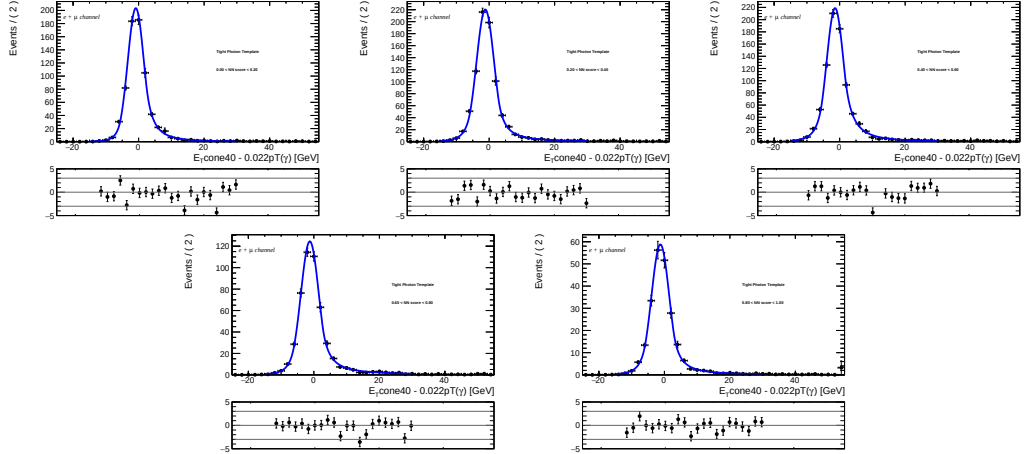


Fig. 6.5: Fits of the isolation distribution for tight photons from Monte Carlo across five bins of the neural network score.

6.5.1.3 Non-tight fit

To construct the jet-faking-photon template, data from a fake-enriched control region, defined by a non-tight photon identification working point, is fit using a Novosibirsk function. The fit minimizes the negative log-likelihood, defined as:

$$-\ln \mathcal{L} = -\ln \prod_i f_{NT}(x|\theta_{NT}) \quad (6.8)$$

where i runs over all events. The non-tight photon templates are displayed in five bins of the neural network score in the control region, characterized by the

presence of jets in the rapidity gap, as shown in Figure 6.6.

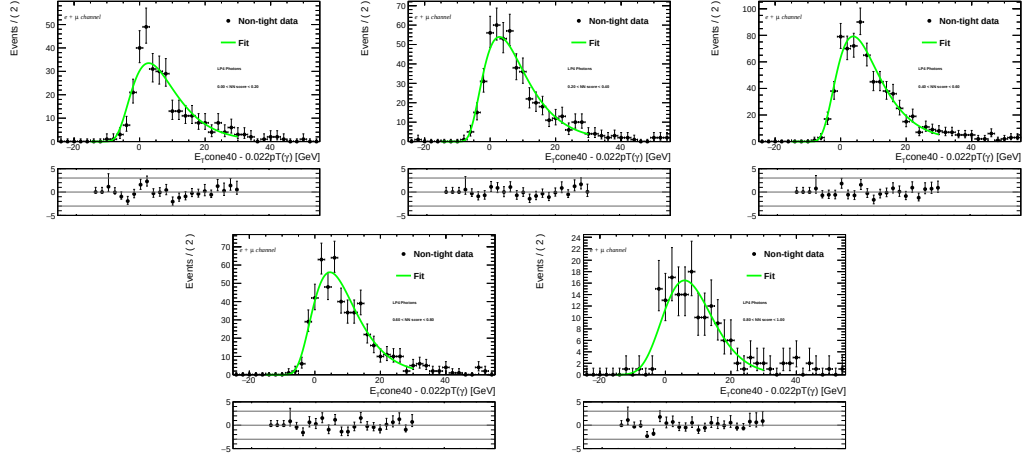


Fig. 6.6: Template fits to the isolation distribution of non-tight data.

6.5.1.4 Resulting fits and differential distributions

Finally the resulting templates are summed and the normalizations fit to data with a tight photon. In this step the template parameters are again floated but constrained by multivariate gaussians defined by the mean and sigma of the best fit values of the template fits. The negative log likelihood is now given by

$$-\ln \mathcal{L} = -\ln \prod_i f_T(x|\theta_T) f_{NT}(x|\theta_{NT}) G(\theta_T|\sigma_{\theta_T}) G(\theta_{NT}|\sigma_{\theta_{NT}}) \quad (6.9)$$

where G are multivariate gaussian constraints and i runs over the number of events. The resulting two component fit in 5 bins of the NN score in the control region defined by the presence of jets in the rapidity gap is shown in Figure 6.7.

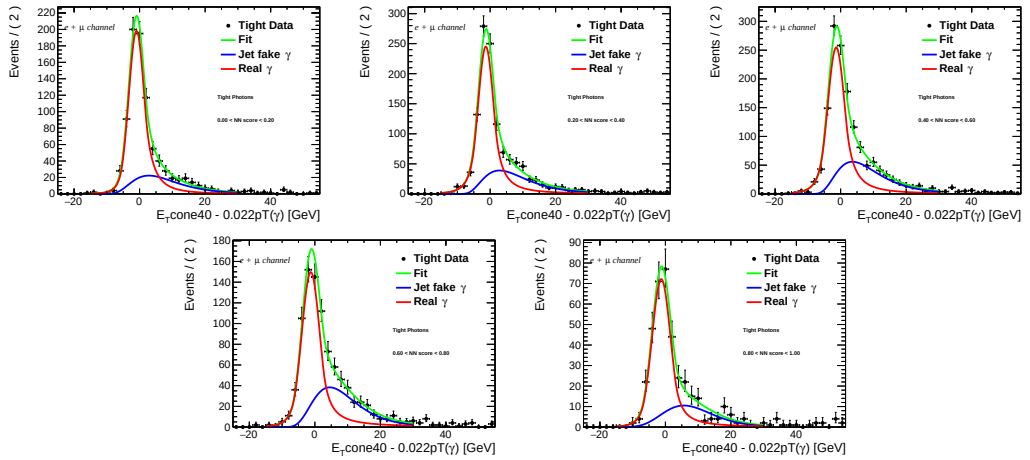


Fig. 6.7: Fit of the normalization for the real photon and fake photon templates to the tight photon data.

6.5.1.5 Jets Faking Photons Differential Distributions

The jet-faking-photon background is estimated using a template fit method. The associated uncertainties include statistical uncertainties from both data and Monte Carlo used in the fit, systematic uncertainties from real photon leakage into the jet-faking-photon control region, variations in the choice of loose photon working points, and uncertainties in the Monte Carlo modelling of real photon isolation. These systematic variations and their uncertainties are quantified using the bootstrapping procedure. The resulting jet-fake-photon yields, utilized in the neural network fit, are shown in Figure 6.8. The ratio panel displays the size of the variation relative to the nominal yield. Note that in the signal region estimation, half of the data is used, with these events being used twice in accordance with the blinding strategy.

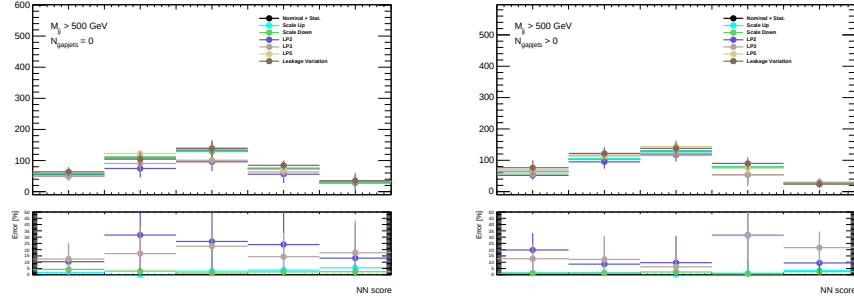


Fig. 6.8: NN score distribution of jet faking photons and associated uncertainties.

As a technical validation, a Monte Carlo closure test was performed. The resulting distribution from the method is smoother and more comparable to other backgrounds in the analysis than the one directly obtained from Monte Carlo, lending confidence to the approach. This comparison is shown in Figure 6.9. Additionally, the template fit method for estimating the number of jets faking photons was cross-checked with an alternative data-driven ABCD method.

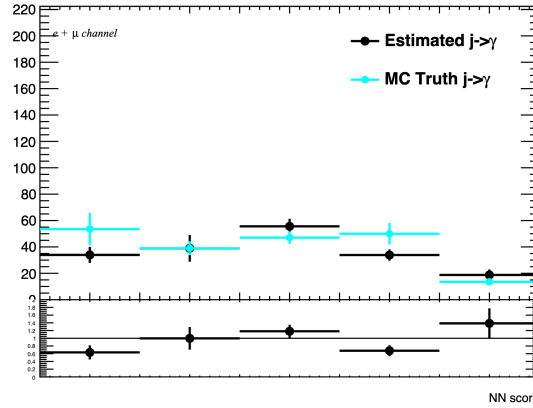


Fig. 6.9: Comparison of the yield of jet faking tight photons in Monte Carlo with predictions derived from the method applied to Asimov data.

The Monte Carlo closure test is limited by the poor modelling of jet-faking photons in the simulation, which initially motivated the adoption of a data-driven method. To further validate the template fit method, an additional ABCD data-driven estimate was employed. The jet-faking photon distributions for signal extraction are shown in Figure 6.10, focusing on electroweak variables in the control regions.

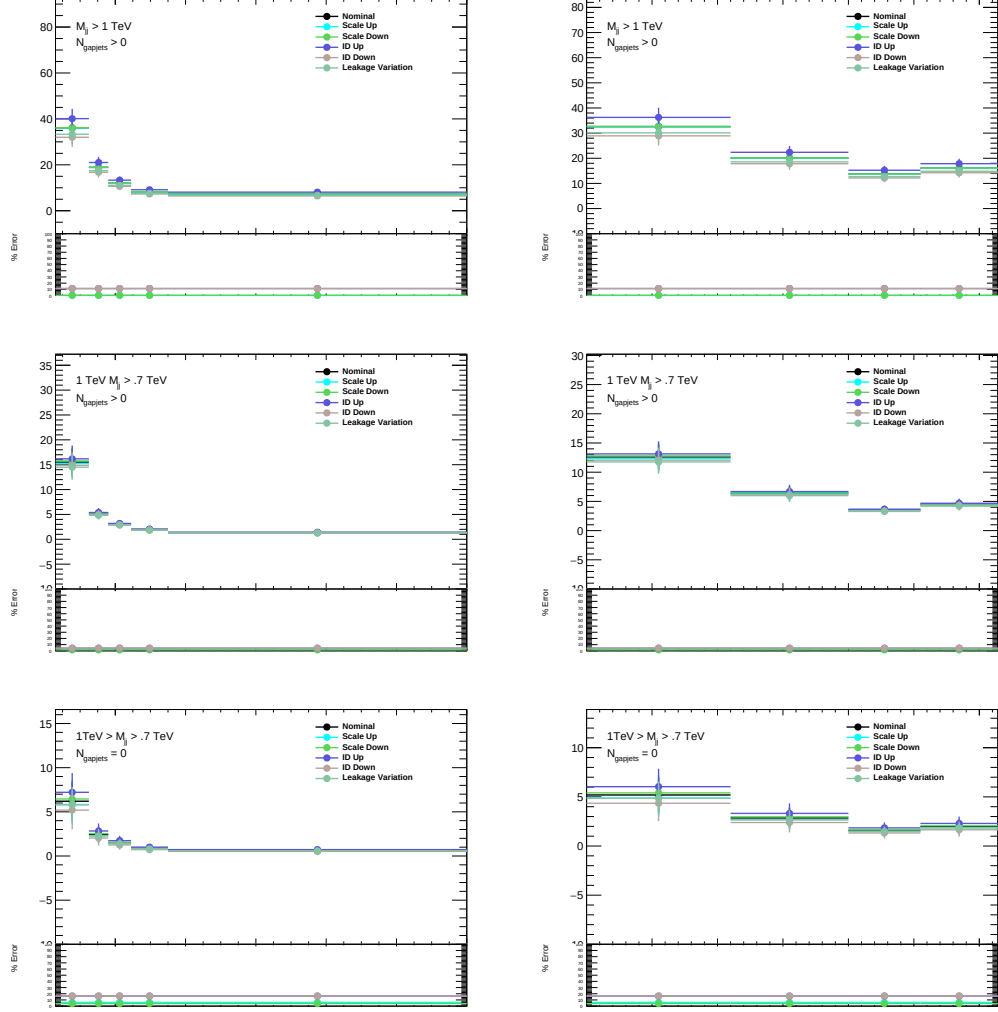


Fig. 6.10: Jet faking photon distributions with systematic uncertainties for $M_{W\gamma}$ and $|\Delta\Phi(l\gamma)|$ in the control regions utilized for differential cross section extraction.

6.5.2 Jet faking leptons

In this analysis, a key background arises from jets misidentified as leptons (electrons or muons), known as “jet faking lepton”. This misidentification complicates precise signal extraction, as mis-reconstructed jets can mimic lepton signatures, especially in high jet activity regions. Monte Carlo (MC) simulations often struggle to model this effect accurately due to the complexity of jet fragmentation

and detector response. To address this, a data-driven fake factor method is utilized to estimate the jet-induced fake lepton contribution, minimizing reliance on MC and controlling systematic uncertainties. Compared to $Z + \text{jets}$ events, dijet events provide higher statistics and greater jet purity, allowing for more robust binned estimations.

6.5.2.1 Fake factor method

The fake factor method is commonly used to estimate the rate of jets misidentified as leptons. Leptons are categorized into three groups: loose, tight, and anti-tight. Loose leptons pass a more relaxed selection, leading to higher jet contamination, while tight leptons undergo stricter isolation and identification cuts, minimizing fake rates. Anti-tight leptons resemble loose leptons but fail certain quality criteria required for tight selection. The fake factor method is based on these classifications and proceeds as follows:

1. Loose and Tight Selection: Events are classified based on whether leptons pass loose or tight selection criteria. Fake leptons predominantly populate the loose sample, while real leptons are concentrated in the tight category.
2. Fake Efficiency (ϵ): The fake efficiency is defined as the ratio of fake leptons passing the tight selection (N_ℓ^{tight}) to those passing the loose selection (N_ℓ^{loose}):

$$\epsilon = \frac{N_\ell^{\text{tight}}}{N_\ell^{\text{loose}}}$$

3. Fake Factor (F): The fake factor represents the probability of a loose lepton being misidentified as a tight lepton and is given by:

$$F = \frac{\epsilon}{1 - \epsilon}$$

4. Fake Background Estimation: The fake background in the signal region is estimated by applying the fake factor to the number of anti-tight leptons in the control region. The anti-tight sample, enriched in fake leptons, is used to estimate the fake yield as:

$$N_\ell^{\text{fake}} = F_\ell \times \left(N_\ell^{\text{anti-tight}} - N_\ell^{\text{anti-tight, prompt}} \right)$$

where $N_\ell^{\text{anti-tight, prompt}}$ represents the prompt lepton contribution, estimated from MC to avoid double-counting real leptons.

The fake factor method provides a data-driven estimation of the fake lepton background for both electrons and muons, reducing uncertainties from jet misidentification and enhancing the precision of $W\gamma + jj$ signal extraction.

For muons, defining tight and anti-tight criteria is essential for accurately estimating the fake background. A sample enriched in fake muons, mostly misidentified jets, is used to derive the fake factor. Tight muons follow the nominal analysis criteria, while anti-tight muons are defined by inverting the isolation or impact parameter significance (σ_{d_0}) cut. The cut $|d_0/\sigma_{d_0}| < 20$ removes outliers while retaining most fake muons. The detailed definitions for tight and anti-tight muons are summarized in Table 6.7.

Table. 6.7: Definitions of tight and anti-tight criteria for muons.

Tight muon	Anti-Tight muon
pass single muon triggers	pass single muon triggers
$p_T > 20$ GeV	$p_T > 20$ GeV
$ \eta < 2.5$	$ \eta < 2.5$
$ z_0 \times \sin \theta < 0.5$ mm	$ z_0 \times \sin \theta < 0.5$ mm
<i>Id_Tight</i>	<i>Id_Tight</i>
<i>Iso_PflowTight_VarRad</i> and $ d_0/\sigma_{d_0} < 3$	<i>fail Iso_PflowTight_VarRad</i> or $3 < d_0/\sigma_{d_0} < 20$

For electrons, both tight and anti-tight categories require $|d_0/\sigma_{d_0}| < 5$. Tight electrons must additionally meet strict isolation and identification criteria, while anti-tight electrons fail either the tight isolation or identification requirements but still pass the baseline selection.

6.5.2.2 Fake factor calculation in dijet region

Dijet data, with its high statistics, is used to estimate the fake factor for muons. The analysis focuses on cases where a jet is misidentified as a muon, requiring the final state to contain a muon and at least one jet. To ensure these are dijet events, the muon and jet are required to be back-to-back, with the jet's transverse momentum exceeding 30 GeV. The fake factor is then calculated as the ratio of events with tight muons to those with anti-tight muons.

Backgrounds from W -boson and Z -boson events are suppressed by applying cuts on missing transverse momentum and the reconstructed transverse momentum of the W -boson. Additional backgrounds, such as top quark and diboson events, are subtracted. The selection criteria are outlined in Table 6.8. Optimized cuts on $\Delta R(\mu, j_0)$ and $\Delta\phi(\mu, j_0)$ are used to maximize the dijet signal-to-background ratio. Figure 6.11 shows the data/MC comparison, where deviations are mainly due to imperfect modelling of fake muons in MC samples, excluding W/Z -jets, are used to estimate the muon fake factor.

Although the distributions focus on the muon channel, similar methods apply to the electron channel.

Table. 6.8: Dijet event selection in the calculation of the fake factor for jet faking muons.

Dijet event selection	
pass single muon triggers	
$N_\mu = 1$ and $p_T^\mu > 20\text{GeV}$	
$N_{jet} \geq 1$ and $p_T^{j_0} > 30\text{GeV}$	
b jet veto	
$E_T^{miss} < 20\text{GeV}$	
$m_T^W < 20\text{GeV}$	
$ \Delta R(\mu, j_0) > 2.8$	
$ \Delta\phi(\mu, j_0) > 2.8$	

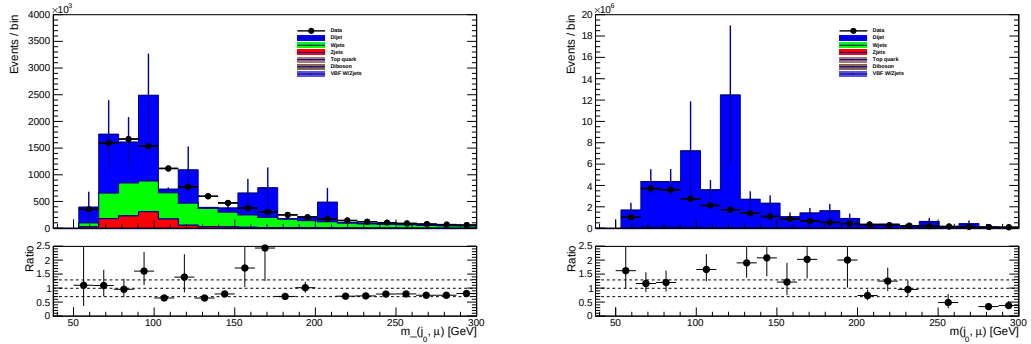


Fig. 6.11: Data/MC comparison in the dijet events enriched region. The left figure displays the distributions for a tight muon selection, while the right figure presents the distributions for an anti-tight muon selection.

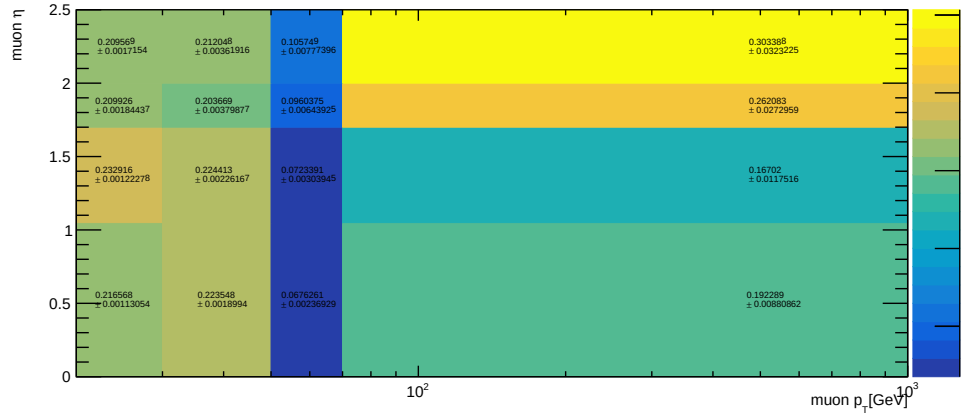


Fig. 6.12: Fake factor for muons in each p_T and η bin.

Figure 6.12 and Table 6.9 show the two-dimensional fake factor for muons, derived from dijet data, binned by transverse momentum (p_T) and pseudorapidity (η). The fake factor is calculated for different p_T and η ranges, as illustrated in Figure 6.12. Each cell in the heatmap represents the fake factor in a specific p_T

	$p_T[20, 30]$	$p_T[30, 50]$	$p_T[50, 70]$	$p_T[70, 1000]$
$\eta[0, 1.05]$	0.216 ± 0.001	0.224 ± 0.002	0.068 ± 0.002	0.192 ± 0.009
$\eta[1.05, 1.7]$	0.233 ± 0.001	0.224 ± 0.002	0.072 ± 0.003	0.167 ± 0.012
$\eta[1.7, 2.0]$	0.210 ± 0.002	0.203 ± 0.004	0.096 ± 0.006	0.262 ± 0.027
$\eta[2.0, 2.5]$	0.210 ± 0.002	0.212 ± 0.004	0.106 ± 0.008	0.303 ± 0.032

Table. 6.9: Fake factor for muon in each p_T and η bin

and η bin, along with its corresponding statistical uncertainty. Table 6.9 provides a detailed representation of the fake factors and their uncertainties for each bin.

6.5.2.3 Sources of Systematic Uncertainty

Several sources of systematic uncertainty affect the estimation of the jet-faking lepton background. Although the following discussion focuses on the muon channel for illustration, similar considerations apply to electrons.

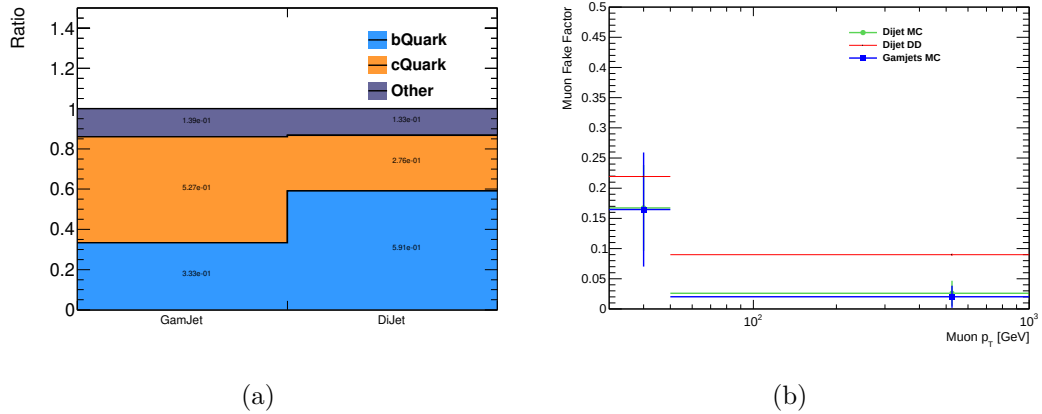


Fig. 6.13: The left figure presents a comparison of lepton composition between dijet and $\gamma + jets$ samples, while the right figure shows the comparison of fake factors for muons between the dijet and $\gamma + jets$ samples.

1. In estimating the lepton fake factor, dijet samples are used as a proxy for $\gamma + jets$ samples. Figure 6.13a shows the composition differences between dijet and $\gamma + jets$ MC samples for leptons, with the corresponding fake factors displayed in Figure 6.13b. The $\gamma + jets$ MC samples are subjected to baseline selections in the lepton channel, ensuring each jet has a transverse momentum of at least 30 GeV. Due to variations in the jet composition ratio, the systematic uncertainty is derived from the fake factor difference between the dijet and $\gamma + jets$ MC samples. This uncertainty is then applied to the nominal value obtained from the data-driven dijet method.

2. In obtaining the fake and anti-tight lepton distributions, QCD $W\gamma$ MC

backgrounds dominate and are subtracted from data. Sherpa QCD $W\gamma$ MC samples are used as the nominal ones, with MadGraph QCD samples serving as cross-checks. The systematic uncertainty is derived from the difference between Sherpa and MadGraph predictions. For $W/Z + jets$ MC samples, uncertainties are estimated by varying scale factors and PDFs, though the PDF uncertainty is found to be negligible.

3. The fake factor calculation in dijet events can be influenced by selection criteria. To assess this impact, variations in missing transverse energy (E_T^{miss}), W boson transverse momentum, and leading jet p_T are tested by shifting the cut values by ± 5 GeV. Table 6.10 summarizes the resulting variations in the fake factor due to these selection changes.

Table. 6.10: Variations of lepton fake factors across p_T bins for various systematic sources.

Fake Factor	$p_T[30, 50]$	$p_T[50, 70]$	$p_T[70, 1000]$
Nominal	0.219 ± 0.001	0.076 ± 0.002	0.201 ± 0.007
MET-down	0.243 ± 0.002	0.085 ± 0.003	0.255 ± 0.010
MET-up	0.199 ± 0.001	0.069 ± 0.001	0.168 ± 0.005
m_T^W -down	0.221 ± 0.001	0.074 ± 0.002	0.206 ± 0.008
m_T^W -up	0.215 ± 0.001	0.077 ± 0.002	0.211 ± 0.007
p_T^{jet} -down	0.219 ± 0.001	0.076 ± 0.002	0.201 ± 0.007
p_T^{jet} -up	0.215 ± 0.001	0.080 ± 0.002	0.203 ± 0.007

4. The binning scheme for lepton p_T and η introduces systematic uncertainty in the fake factor calculation. To evaluate this, an alternative binning scheme was applied, and the variation from the nominal fake factor is treated as an additional systematic uncertainty. The alternative binning scheme and the corresponding fake factors are provided in Table 6.11.

6.5.2.4 Validation

To validate the estimation of jet-induced fake leptons, a validation region was defined by inverting the E_T^{miss} and W_m^T cuts ($E_T^{miss} < 30$ GeV, $W_m^T < 30$ GeV). The distributions of m_{jj} and p_T^ℓ in this region are shown in Figure 6.14, and the yield comparison is summarized in Table 6.12.

6.5.2.5 Estimated yields in Signal and Control regions for muon channel

The fake factor for jet-induced muon fakes, estimated from dijet events, is applied to both the signal and control regions of VBS $W\gamma jj$. Combined with the aforementioned systematic uncertainties, the distributions and yields are shown in

Table. 6.11: Lepton fake factor for an alternative p_T binning scheme.

	$\eta[0, 1.05]$	$\eta[1.05, 1.7]$	$\eta[1.7, 2.0]$	$\eta[2.0, 2.5]$
$p_T[20, 30]$	0.217 ± 0.001	0.233 ± 0.001	0.210 ± 0.002	0.210 ± 0.002
$p_T[30, 40]$	0.273 ± 0.003	0.271 ± 0.003	0.224 ± 0.005	0.229 ± 0.004
$p_T[40, 50]$	0.135 ± 0.003	0.136 ± 0.003	0.154 ± 0.006	0.166 ± 0.007
$p_T[50, 60]$	0.062 ± 0.003	0.068 ± 0.003	0.092 ± 0.007	0.096 ± 0.008
$p_T[60, 70]$	0.086 ± 0.005	0.086 ± 0.007	0.109 ± 0.015	0.144 ± 0.019
$p_T[70, 80]$	0.126 ± 0.010	0.117 ± 0.013	0.200 ± 0.032	0.200 ± 0.037
$p_T[80, 1000]$	0.287 ± 0.016	0.243 ± 0.022	0.360 ± 0.050	0.481 ± 0.060

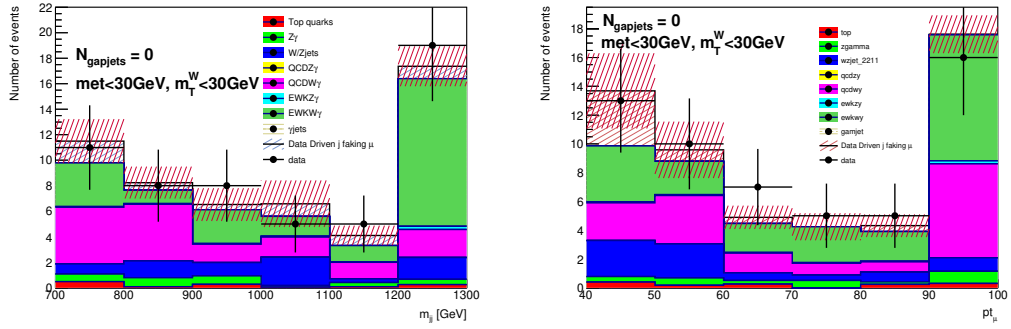


Fig. 6.14: The distributions of data, MC samples, and data-driven jet faking muons in the validation region.

Table. 6.12: Total estimated yields of fake muons and other MC background contributions in the validation region.

Muon Channel	Yield
Truth MC	49.21 ± 3.39
Fake Electron	5.50 ± 1.84
Data	56 ± 7.48

Figures 6.15 and 6.16. The yields, along with their associated uncertainties, are provided in Tables 6.13 and 6.14.

6.5.2.6 Estimated yields in Signal and Control regions for electron channel

The background contribution from fake electrons is estimated by applying the electron fake factor to the respective anti-tight regions. To account for the prompt electron contamination in these regions, the contribution from real electrons is subtracted using a Monte Carlo (MC) based estimation, where real electrons are identified through truth-level information.

The the estimated fake electron yields and corresponding sources of system-

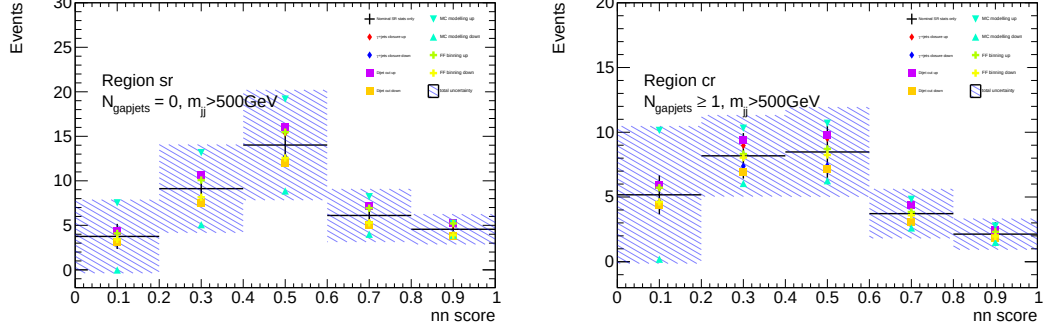


Fig. 6.16: Distributions of fake muons in the NN score for the signal region.

Table. 6.14: Estimated yields for NN score distributions with one bin for the background from misidentified leptons, along with their associated systematic uncertainties. The nominal yield is presented in the first column following the region column. The subsequent columns detail the separate contributions of statistical uncertainty, systematic uncertainty from $\gamma + Jet$ closure, systematic uncertainty from QCD modelling with two different generators, systematic uncertainty from dijet selections, and systematic uncertainty related to different p_T binning strategies.

Muon channel	Nominal yield	Stat.	Closure	MC	Selection	Binning	Total uncertainty
sr	31.62	3.14	3.60	14.06	4.86	3.04	21.20
cr	26.36	3.3	2.98	6.19	4.04	0.10	9.88

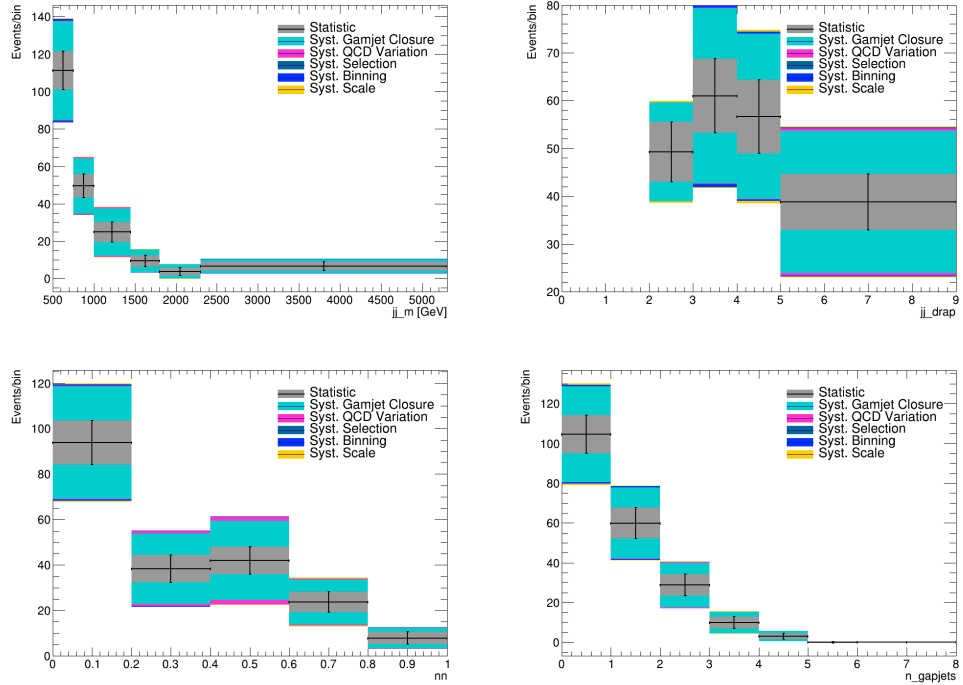


Fig. 6.17: Fake electron contributions for m_{jj} , ΔY_{jj} , NN score, and $n_{gapjets}$. The plots are presented with systematic terms included in stacked format.

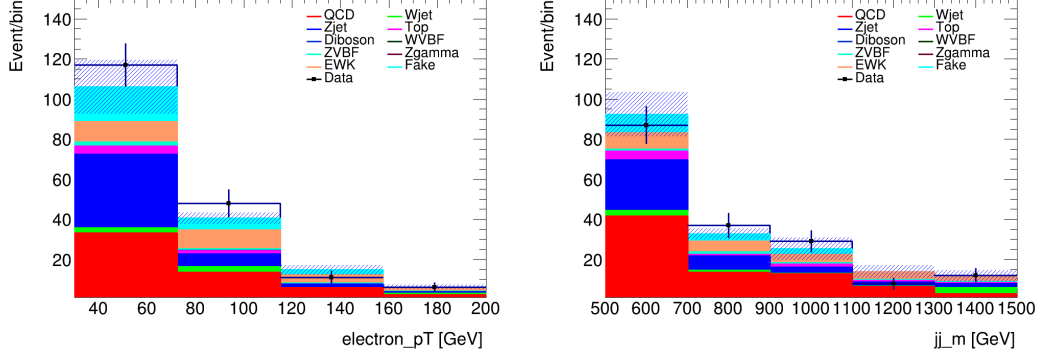


Fig. 6.18: Estimation of the fake electron distribution in the validation region using the fake factor method. The left shows the distribution versus electron, while the right displays the distribution versus m_{jj} .

Table. 6.15: Total estimated yields of fake electrons and other MC background contributions in the validation region.

electron channel	Yield
Truth MC	141.59 ± 13.67
Fake electron	25.95 ± 3.26
Data	182.0 ± 13.49

6.5.3 Lepton Faking Photons

6.5.3.1 Introduction

From Figures 6.19 and 6.20, even after baseline selections, many misidentified photons remain in the $Z + \text{jets}$, $W + \text{jets}$, and diboson MC samples. The truth classifications show that these misidentified photons are primarily electrons or background photons. Background photons mainly originate from light mesons, such as π^0 , and FSR photons, which are accounted for by the jet-faking photon estimate. In the electron channel, many isolated electrons in $Z + \text{jets}$ MC samples are misidentified as photons.

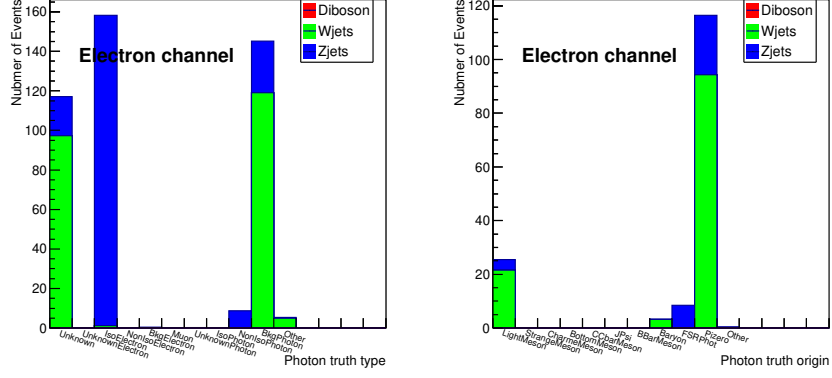


Fig. 6.19: On the left is the distribution of truth types for photons in Zjets, Wjets, and Diboson MC samples for the electron channel after baseline selections. On the right is the distribution of truth origins for photons classified as photons in Zjets, Wjets, and Diboson MC samples for the electron channel after baseline selections.

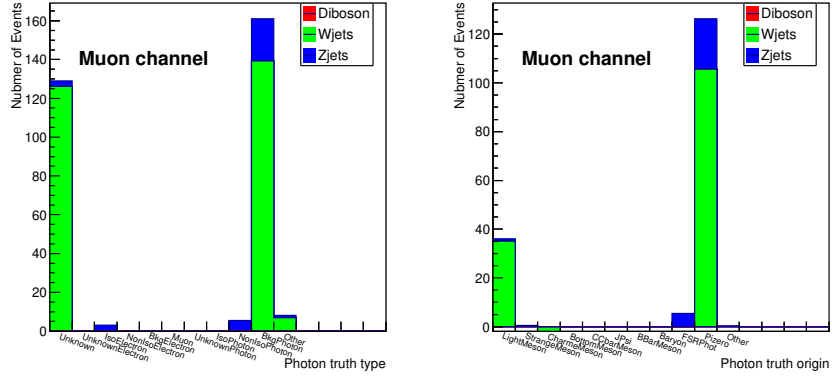


Fig. 6.20: On the left is the distribution of truth types for photons in Zjets, Wjets, and Diboson MC samples for the muon channel following baseline selections. On the right is the distribution of truth origins for photons identified as photons in Zjets, Wjets, and Diboson MC samples for the muon channel after baseline selections.

Photons may be mis-reconstructed or misidentified as electrons due to tracking inefficiency or poor matching between the track and the energy cluster in the calorimeter, as discussed in [171]. To estimate this contribution, a data-driven method is used instead of relying on MC. This involves measuring the electron-to-photon fake rate and applying it to a control region where one or both photon selections are replaced with analogous electron selections. The fake rate measurement requires two additional control regions: one enriched with real electrons and the other with electron-to-photon fakes. The fake rate is defined as:

$$F_{e \rightarrow \gamma} = \frac{N_{\gamma}^{reco} / N_e}{N_e^{reco} / N_e} = \frac{\epsilon_{\gamma}}{\epsilon_e} \quad (6.10)$$

where N_{γ}^{reco} and N_e^{reco} represent the number of events in the fake-enriched and real-enriched regions, respectively, and ϵ_{γ} and ϵ_e are the identification efficiencies for photons and electrons. The fake rate is applied to a control region where the signal region selection is modified by replacing photons with electrons having similar p_T , isolation, and identification criteria. Since the fake rate depends on the identification efficiencies of both photons and electrons, the object selection and trigger requirements in the regions where the fake factor is calculated must match those in the control region where it is applied, as well as the photon requirements in the signal region.

6.5.3.2 Selection

CRee and CReg: The real and fake enriched control regions are defined by selecting a Z boson using a tag-and-probe method, similar to the one used for the fake factor calculation. The tag electron must be matched to the lowest unscaled single electron trigger, and the probe is either an electron or a photon. These regions are referred to as CRee and CReg, respectively. The p_T cut for the tag electron is set to 30 GeV to ensure high trigger efficiency, while the p_T cut for the probe electron is lowered to 22 GeV to align with the photon selection. In both CRee and CReg, events containing additional baseline electrons or photons are vetoed to avoid ambiguity regarding the origin of the Z boson and to prevent overlap with the control region where the fake rate is applied. The detailed selections are shown in Table 6.16.

Table. 6.16: Definitions of tag-and-probe electrons and probe photons.

Tag electron	Probe electron	Probe photon	Other selections
$p_T > 30\text{GeV}$	$p_T > 22\text{GeV}$	$p_T > 22\text{GeV}$	$m_T^{W(e\nu)} < 20\text{GeV}$
$ \eta < 2.5$	$ \eta < 2.37$	$ \eta < 2.37$	$E_T^{\text{miss}} < 20\text{GeV}$
e_isoTightVarRad	e_isoTightVarRad	gam_isoTight	
e_idTight	e_idTight	gam_idTight	
$ z_0 \times \sin \theta < 5\text{mm}$	$ z_0 \times \sin \theta < 5\text{mm}$		
$ d_0/\sigma_{d_0} < 3$	$ d_0/\sigma_{d_0} < 3$		
pass single electron triggers	opposite charge with tag electrons		

6.5.3.3 Fake Rate Estimation

For $Z \rightarrow ee$ decays, each electron may be reconstructed as a photon. The tag-and-probe method requires that the final state includes at least one electron passing the “tag” selection. If the total number of $Z \rightarrow ee$ events is N , then after reconstruction, the number of events with two electrons is N_{ee}^{reco} , the number of events with one electron and one photon is $N_{e\gamma}^{\text{reco}}$, and the number of events with two photons is $N_{\gamma\gamma}^{\text{reco}}$.

$$N_{ee} = N_{ee}^{reco} + N_{e\gamma}^{reco} + N_{\gamma\gamma}^{reco} \quad (6.11)$$

$$N_{e_{tag}e_{tag}}^{reco} = \epsilon_e^2 N_{e_{tag}e_{tag}} \quad (6.12)$$

$$N_{e_{tag}e_{probe}}^{reco} = \epsilon_e^2 N_{e_{tag}e_{probe}} \quad (6.13)$$

$$N_{e_{tag}\gamma_{probe}}^{reco} = \epsilon_e \epsilon_\gamma (2N_{e_{tag}e_{tag}} + N_{e_{tag}e_{probe}}) \quad (6.14)$$

$$F_{e \rightarrow \gamma} = \frac{\epsilon_\gamma}{\epsilon_e} = \frac{N_{e_{tag}\gamma_{probe}}^{reco}}{2N_{e_{tag}e_{tag}}^{reco} + N_{e_{tag}e_{probe}}^{reco}} \quad (6.15)$$

In the above formulas, the subscript “tag” indicates that the particle passes the “tag” selection, while the subscript “probe” indicates that the particle passes the “probe” selection. Since the “tag” selection is stricter than the “probe” selection, particles passing the “probe” selection can also pass the “tag” selection. Based on this, the fake factor for electrons faking photons is calculated by dividing the number of events with one photon and one electron by the number of events with two electrons. Notably, for events where both electrons can pass the “tag” selection, their weights must be doubled.

The fake rate is measured in 25 bins, divided into 5 bins in the probe’s p_T and 5 bins in $|\eta|$. For each bin, a fit to the invariant mass of both objects is performed to estimate the signal and background contributions. A double-sided crystal ball function is used for the signal, and an exponential function is used for the background. The shape parameters and normalizations of both functions are floated during the fit. In cases where the probe also meets the tag criteria in CRee, both electrons can potentially fake a photon, contributing to the denominator of the fake rate. A separate set of histograms and fits is calculated by swapping the tag and probe roles for events where the probe also passes the tag criteria. All fits are shown in Figures 6.21 and 6.22. The fits are performed within ± 20 GeV around the Z mass peak at 91.118 GeV, and the signal is integrated within a 10 GeV window around the Z mass peak. The final fake rate, along with statistical uncertainties from the fit yields, is presented in Figure 6.23 and Figure 6.24.

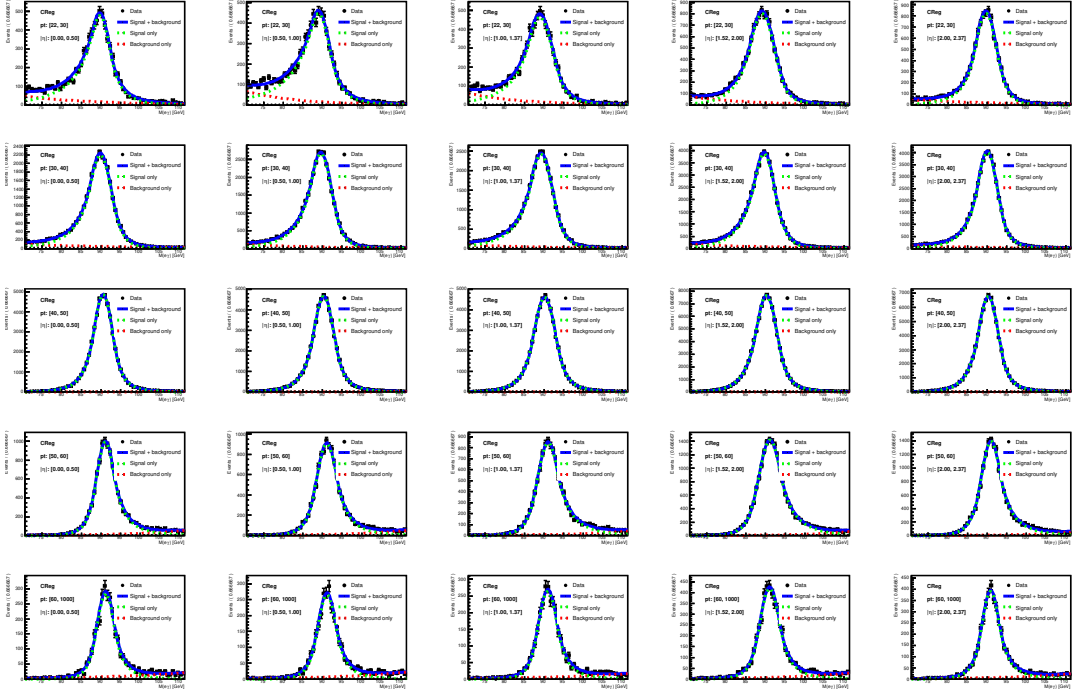


Fig. 6.21: Signal and background fits for each probe electron in terms of $|\eta|$ and p_T bins in the CReg.

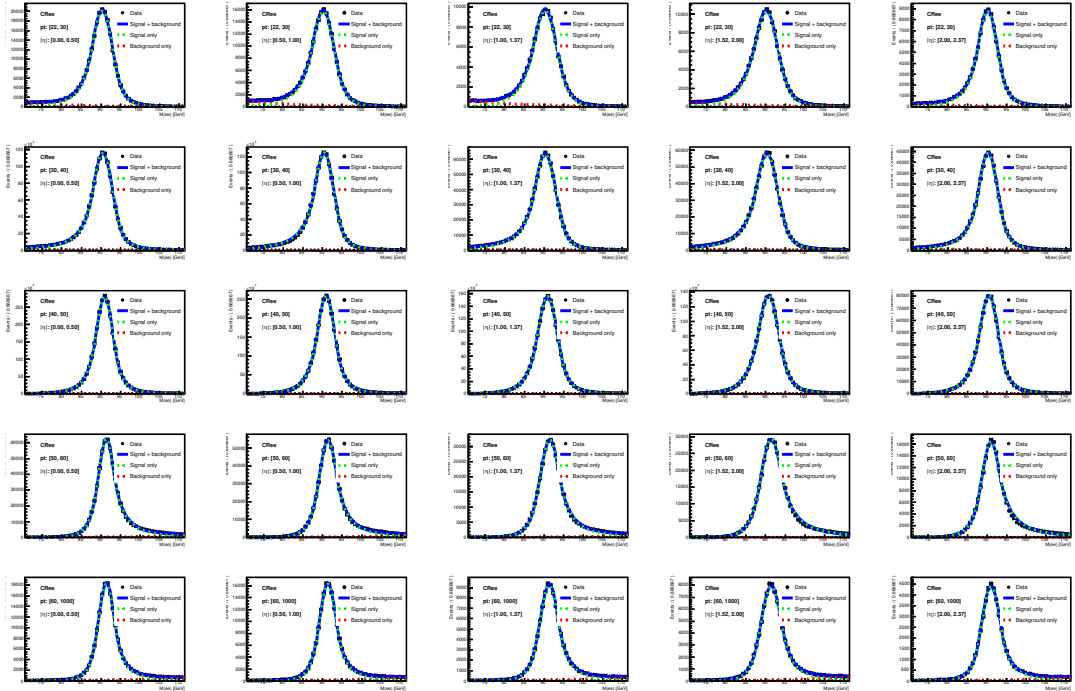


Fig. 6.22: Signal and background fits for each probe electron categorized by $|\eta|$ and p_T bins in CReg.

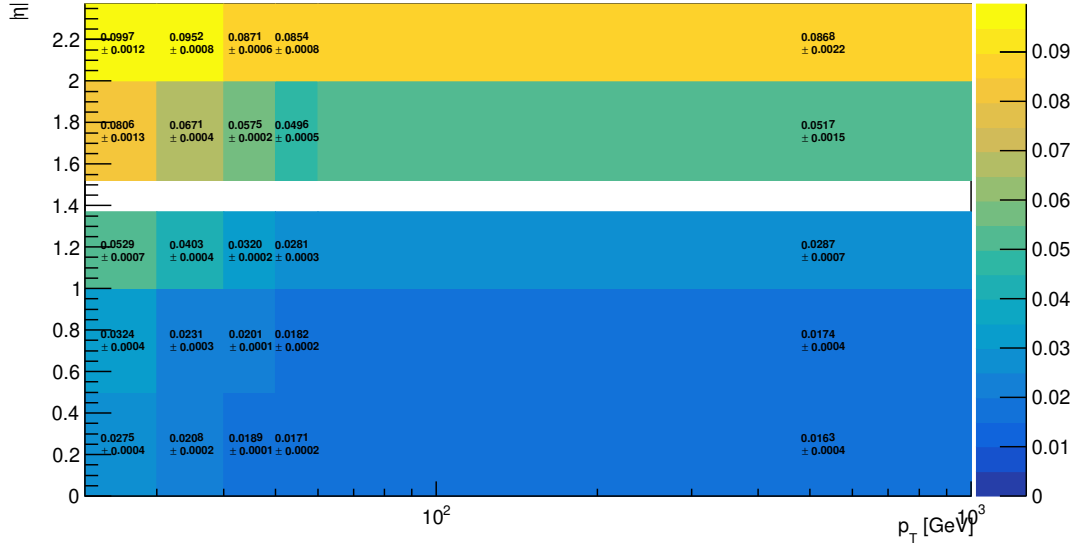


Fig. 6.23: Nominal 2D electron-to-photon fake rate, incorporating statistical uncertainty.

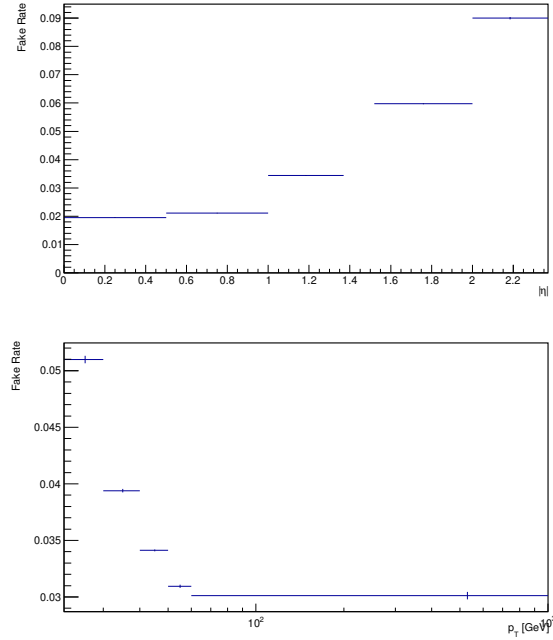


Fig. 6.24: Nominal electron-to-photon fake rate as a function of p_T and η , including statistical uncertainty.

Table 6.17 and Table 6.18 present the definitions of tag and probe electrons in the electron and muon channels, respectively. Events containing one tag electron/muon and one probe electron are selected, and a 2D fake factor is applied based on the probe electron's p_T and η . If the probe electron also satisfies the tag selection in the electron channel, the event weights should be multiplied by 2. It is

important to note that the reconstruction of the W boson utilizes the information from the tag lepton with the higher p_T .

Table. 6.17: Definitions of signal and probe electrons in the electron channel.

Signal electron	probe electron	Other selections
$p_T > 30\text{GeV}$	$p_T > 22\text{GeV}$	$m_T^{W(e\nu)} > 30\text{GeV}$
$ \eta < 2.5$	$ \eta < 2.37$	$E_T^{miss} > 30\text{GeV}$
$ z_0 \times \sin \theta < 5\text{mm}$	$ z_0 \times \sin \theta < 5\text{mm}$	$N_{jet} \geq 2$
$ d_0/\sigma_{d_0} < 3$	$ d_0/\sigma_{d_0} < 3$	$p_T^{j0} > 50\text{GeV}$
e_isoTightVarRad	e_isoTightVarRad	$p_T^{j1} > 50\text{GeV}$
e_idTight	e_idTight	$m_{jj} > 500\text{GeV}$
pass single electron triggers		$ M_Z - M_{ee} > 10\text{GeV}$

Table. 6.18: Definitions of signal muons and probe electrons in the muon channel.

Signal muon	probe electron	Other selections
$p_T > 30\text{GeV}$	$p_T > 22\text{GeV}$	$m_T^{W(\mu\nu)} > 30\text{GeV}$
$ \eta < 2.5$	$ \eta < 2.37$	$E_T^{miss} > 30\text{GeV}$
$ z_0 \times \sin \theta < 0.5\text{mm}$	$ z_0 \times \sin \theta < 5\text{mm}$	$N_{jet} \geq 2$
$ d_0/\sigma_{d_0} < 3$	$ d_0/\sigma_{d_0} < 3$	$p_T^{j0} > 50\text{GeV}$
mu_isoPflowTight_VarRad	e_isoTightVarRad	$p_T^{j1} > 50\text{GeV}$
mu_idTight	e_idTight	$m_{jj} > 500\text{GeV}$
pass single muon triggers		

6.5.3.4 Systematics

The electron-to-photon fake estimate is entirely data-driven. Five sources of systematic uncertainties are considered:

- Fitting range variation: The fitting range is adjusted by ± 5 GeV on each side.
 - Nominal: 71 - 111 GeV
 - Up variation: 66 - 116 GeV
 - Down variation: 76 - 106 GeV
- Integration window variation: The integration window is varied by ± 5 GeV.
 - Nominal: 81 - 101 GeV
 - Up variation: 76 - 106 GeV
 - Down variation: 86 - 96 GeV
- η binning variation: The fake rate's η binning is modified by adding or removing 2 bins, excluding the calorimeter crack region (1.37 to 1.52).

- Nominal: 0.0 - 0.5 - 1.0 - 1.37/1.52 - 2.0 - 2.37
- Up variation: 0.0 - 0.33 - 0.66 - 1.0 - 1.37/1.52 - 1.8 - 2.1 - 2.37
- Down variation: 0.0 - 0.7 - 1.37/1.52 - 2.37
- p_T binning variation: The fake rate's p_T binning is varied by adding or removing 2 bins.
 - Nominal: 22 - 30 - 40 - 50 - 60 - 1000
 - Up variation: 22 - 27 - 33 - 38 - 45 - 55 - 65 - 1000
 - Down variation: 22 - 35 - 50 - 1000
- Fitting function variation: The signal and background fitting functions are individually varied.
 - Nominal: Double-sided crystal ball for signal and exponential for background
 - Signal variation: Gaussian with double-sided exponential for signal and exponential for background
 - Background variation: Double-sided crystal ball for signal and 4th order Bernstein polynomial for background

6.5.3.5 Validation

The method is validated in the electron-to-photon fake-enriched Z veto region, where the invariant mass of the electron and photon is between 81.18 GeV and 101.18 GeV in the electron channel. To estimate the fake contribution in this region, the fake rate is applied to the CRee control region with the Z veto inverted. Additionally, the E_T^{miss} and m_T^W cuts are inverted ($E_T^{miss} < 30$ GeV, $W_m^T < 30$ GeV). The m_{jj} distributions in four regions, divided by centrality and number of gap jets, are shown with statistical and systematic uncertainties in Figure 6.25 and Table 6.19.

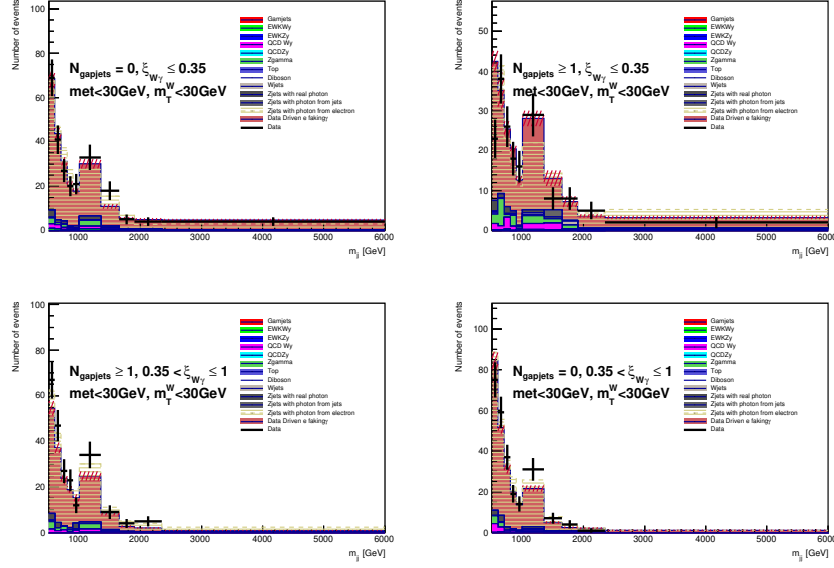


Fig. 6.25: Comparison of data and MC plus data-driven results in the validation region.

Table. 6.19: Yields of data, data-driven electron-to-photon fakes, and MC samples with true photons in the low E_T^{miss} and Z veto control region.

Region	Data	Data-driven e fake γ	MC truth photon
sr	242 ± 15.55	205.224 ± 5.32	32.3136 ± 3.12
cra	173 ± 13.15	148.631 ± 4.00	42.6491 ± 5.37
crb	228 ± 15.10	160.666 ± 4.51	27.6622 ± 3.41
crc	247 ± 15.72	204.586 ± 5.69	28.9682 ± 3.44

6.5.3.6 Estimation in Signal and control regions

The comparison plots between the data-driven estimation of electron faking photons and MC samples, including $Z + \text{jets}$, $W + \text{jets}$, and diboson events where the true origin of the photons is electrons after baseline selections, are shown in Figures 6.26, 6.27, 6.28, and 6.29. In both the signal and control regions with the Z veto cut, the data-driven results show more electron faking photon events compared to the three MC samples, both in the electron and muon channels. This suggests that the MC samples underestimate the electron faking photon background.

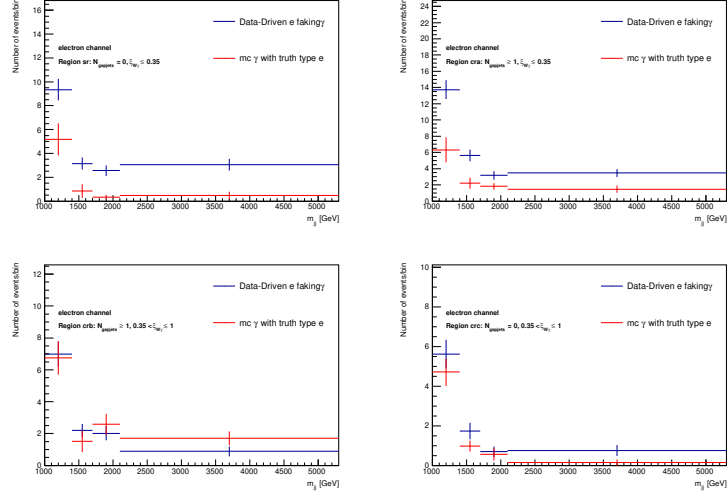


Fig. 6.26: m_{jj} distributions of electron-to-photon fakes estimated in the signal and control regions of the electron channel.

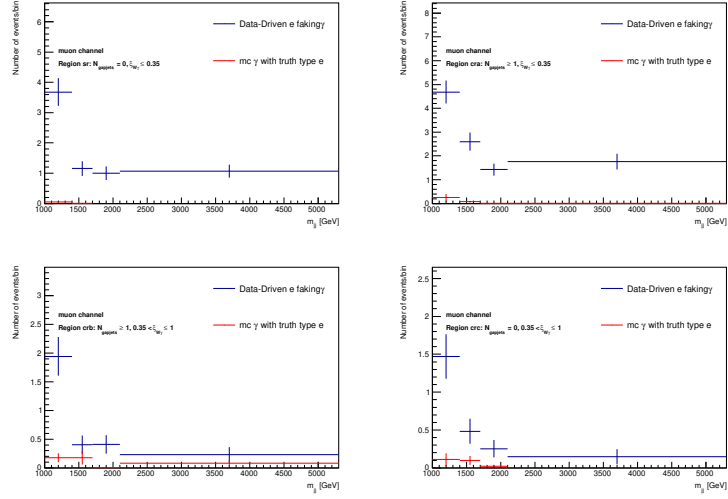


Fig. 6.27: m_{jj} distributions of electron-to-photon fakes estimated in the signal and control regions of the muon channel.

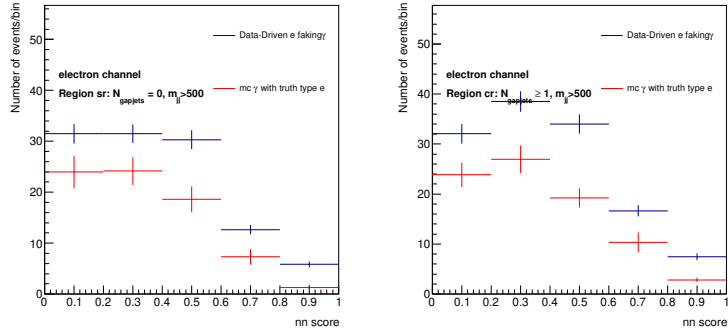


Fig. 6.28: NN score distributions of electron-to-photon fakes estimated in the signal and control regions of the electron channel.

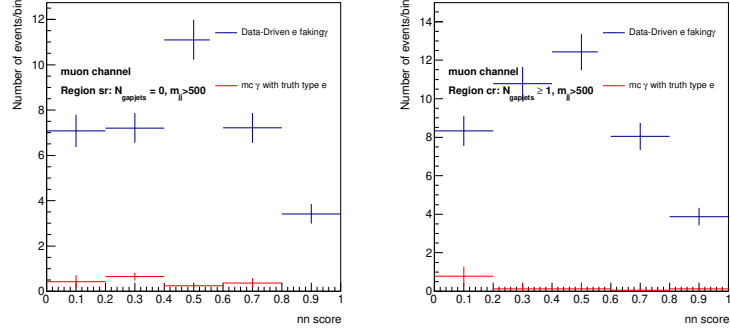


Fig. 6.29: NN score distributions of electron-to-photon fakes estimated in the signal and control regions of the muon channel.

6.5.4 Pileup Background

Unlike lepton selection, there is no explicit requirement on the photon's point of origin, as this is not well measured in most events. Thus, a photon from a different pp interaction in the same LHC bunch crossing could combine with a $W + \text{jet}$ event from the primary vertex, faking a signal event. In Monte Carlo simulations, truth information for pileup overlay events is not stored, resulting in pileup photons being assigned a truth type and origin of 0 by the MC truth classifier tool. Reconstructed photons may also have truth type and origin 0 if they are radiated at large angles from jets, thus failing truth matching. To avoid using such events, the background from pileup photons is estimated using a data-driven method. This method is based on the technique developed in the $Z(l\ell)\gamma$ analysis [172].

The key assumption of the data-driven method is that the distribution of the difference between the z position of the primary vertex and the photon z obtained from calorimeter pointing will differ for pileup photons and those from the hard scatter. To minimize the impact of photon pointing resolution, only converted photons with hits in the silicon pixel detector are used, as these provide much better resolution. This is demonstrated in Figure 6.30, where the photon pointing resolution is shown in data for a control region, comparing photons with and without hits in the pixel tracker. Photons with good resolution exhibit a much sharper peak in $\Delta z(\gamma, \text{PV})$.

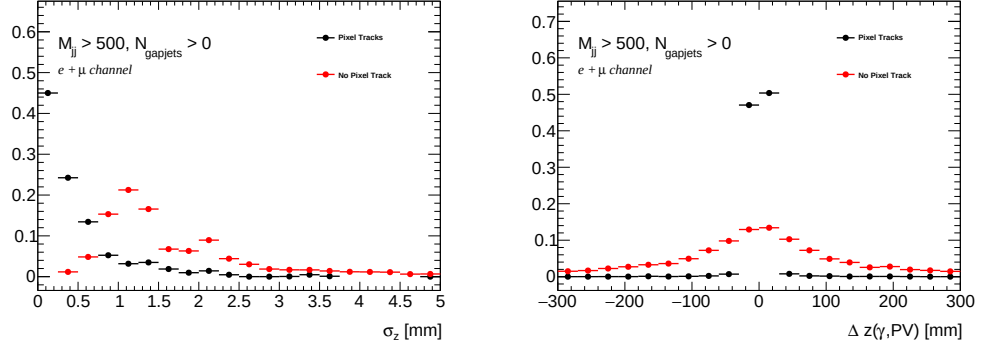


Fig. 6.30: Photon pointing resolution and Δz between the photon pointing z and the primary vertex for converted photons matched with pixel tracks, as well as for photons without pixel tracks.

The $\Delta z(\gamma, PV)$ distribution in data in the control region ($N_{gapjets} > 0$) is shown in Figure 6.31.

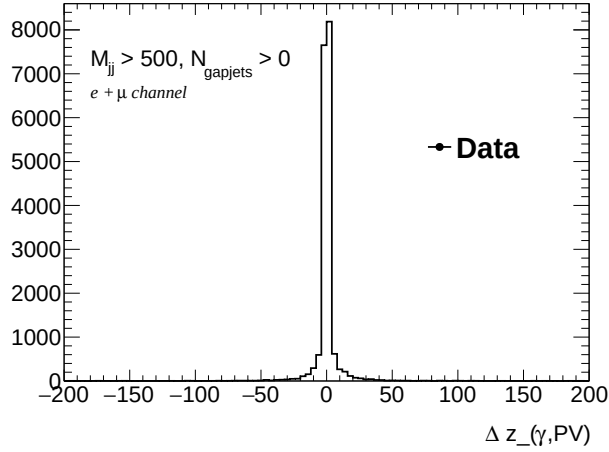


Fig. 6.31: $\Delta z(\gamma, PV)$ in the control region of the data.

The $\Delta z(\gamma, PV)$ distribution is sharply peaked at 0, indicating that good resolution photons have been selected and that most reconstructed photons originate from the hard scatter. However, for pileup photons, the $\Delta z(\gamma, PV)$ distribution is the difference between two uncorrelated Gaussian distributions, each with a width of 35 mm (the longitudinal spread of photon bunches in the LHC). Thus, the resulting distribution is expected to be a Gaussian with a width of $35 \text{ mm} \times \sqrt{2} = 50 \text{ mm}$. This has been confirmed by generating toy models based on Gaussians with a 35 mm width and fitting the difference of the resulting distributions.

Using the Gaussian properties of the pileup distribution, the fraction of pileup events in data can be calculated as:

$$f_{PU} = \frac{N_{data}^{|\Delta z| > 50 \text{ mm}} - N_{MC}^{|\Delta z| > 50 \text{ mm}} \times C}{N_{data} \times 0.32} \quad (6.16)$$

where C is a normalization factor derived by comparing the QCD $W\gamma$ and EW $W\gamma$ to data. To validate that only a normalization factor is required, the shape of the two Monte Carlo samples is compared with data in Figure 6.32. No mismodelling of the $\Delta z(\gamma, PV)$ distribution is observed in the QCD sample. A discrepancy is noted in the signal sample, but this comparison is performed in a control region with few signal events. Once data is unblinded, signal samples can be used for this estimate in the signal region.

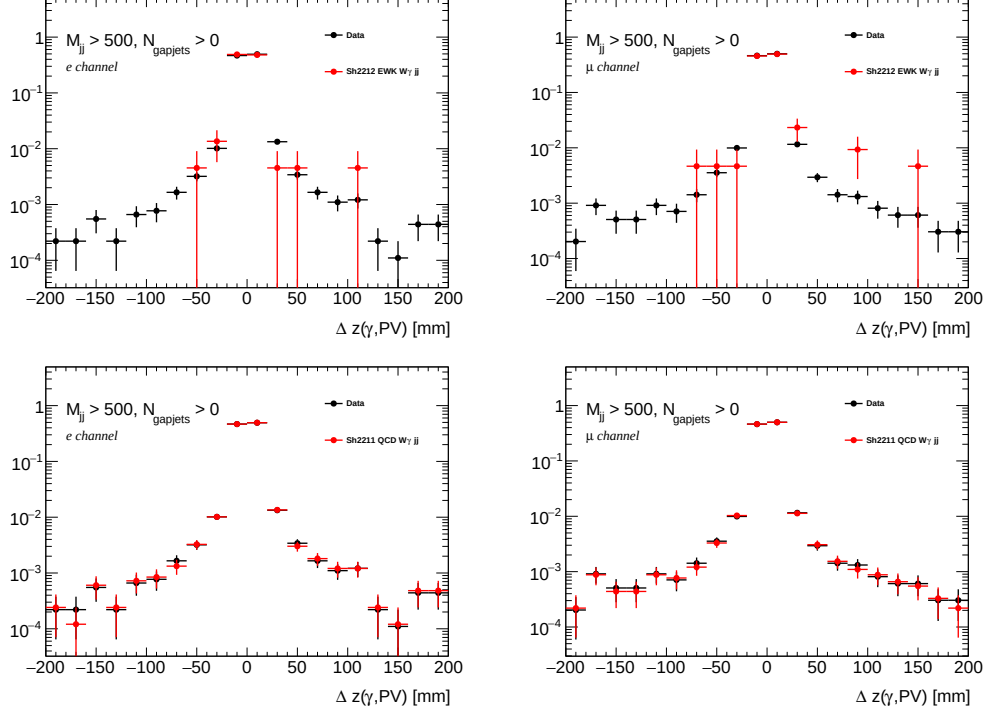


Fig. 6.32: Modelling of $\Delta z(\gamma, PV)$ in the Sherpa EWK $W\gamma jj$ sample and the QCD $W\gamma jj$ sample.

In the control region, the normalization factor is determined to be 1.58 ± 0.08 , which is consistent with the factor used in the inclusive $Z\gamma$ analysis [172]. The result of the pileup fraction calculation is:

$$f_{pu} = 0.79 \pm 0.70\% \quad (6.17)$$

The pileup background includes a component where the pileup photon is misreconstructed from a pileup jet. This component is already accounted for in the data-driven estimate of jets faking photons. To avoid double counting, the jet-faking photon estimate is performed on a sample of inclusive prompt photon events from data recorded using prescaled single-photon triggers. The photon purity in this sample is assumed to be the same as in pileup events. Photons in this sample are required to pass the same baseline selection and must convert in the silicon

pixel tracker. The photon purity in this sample is found to be $56.7 \pm 0.1\%$.

Applying the photon purity to the pileup fraction calculated earlier, the fraction of pileup photons in data is found to be $0.45 \pm 0.39\%$. This fraction is applied to data after subtracting non-prompt backgrounds. Before unblinding, this calculation is performed and applied only in the control region for the neural network fit. In high M_{jj} control regions, the pileup fraction is consistent with zero due to larger statistical uncertainties from the limited number of high-resolution photons. The pileup fraction will be calculated in the signal region after unblinding.

6.6 Systematics

Beyond the systematic uncertainties in the data-driven background estimates discussed in 6.5, additional systematics affecting Monte Carlo predictions are included. These are split into two main types: theoretical uncertainties, impacting both the shape and normalization of the background and signal MC samples, and experimental uncertainties, which influence the event reconstruction. The treatment of these uncertainties is outlined in this section.

6.6.1 Smoothing

To reduce the effect of statistical fluctuations in systematic variations on the final fit, a smoothing procedure is applied. The steps of this algorithm are as follows:

1. A threshold δM is defined based on the statistical uncertainties of both the systematic variation and the nominal sample.
2. For each bin i and its neighbor $i - 1$, compute:

$$x_{i-1,i} = \left| \frac{S_i - N_i}{N_i} - \frac{S_{i-1} - N_{i-1}}{N_{i-1}} \right| \quad (6.18)$$

and the relative statistical uncertainty:

$$\delta x_{i-1,i} = \sqrt{\frac{\delta M_i^2}{N_i^2} + \frac{\delta M_{i-1}^2}{N_{i-1}^2}}, \quad (6.19)$$

where S_i and N_i represent the number of events in bin i for the systematic variation and the nominal sample, respectively.

3. If $x_{i-1,i} < \delta x_{i-1,i}$ for any bin, the neighboring bins $b - 1$ and b with the largest ratio $\frac{\delta x_{b-1,b}}{x_{b-1,b}}$ are merged.
4. This process continues until no bin satisfies $x_{i-1,i} < \delta x_{i-1,i}$.

5. Finally, the TH1 Smooth algorithm, as described in Ref. [173], is applied.

For correlated event sources, δM is defined as $\delta M = \max(\delta S, \delta N)$, while for uncorrelated sources, $\delta M = \sqrt{\delta S^2 + \delta N^2}$. Here, δS and δN are the statistical uncertainties on the systematic variation and the nominal sample, respectively.

6.6.2 Theory Uncertainties

Theoretical uncertainties are taken into account for the Monte Carlo samples used for both signal and background. Each sample includes at least two systematic sources: uncertainties from missing higher-order corrections in cross-section calculations, and uncertainties tied to the PDFs used during event generation. For NLO-calculated backgrounds, such as QCD $W\gamma jj$ and QCD $Z\gamma jj$, an additional uncertainty related to the strong coupling constant α_S is also considered. Additionally, a MadGraph QCD sample is provided alongside the nominal Sherpa QCD sample, and the variation between their predictions is included as an uncertainty.

6.6.2.1 Scale Uncertainties

The impact of missing higher-order corrections in the partonic cross-section expansion is evaluated by applying scale variations. Both the renormalization and factorization scales are varied by a factor of two, providing an estimate for the next-order contributions to the cross-section. For each Monte Carlo sample, six scale combinations are evaluated: $(\mu_F, \mu_R) = (0.5, 0.5), (0.5, 1.0), (1.0, 0.5), (1.0, 2.0), (2.0, 1.0)$, and $(2.0, 2.0)$. Off-diagonal scale combinations, such as $(\mu_F, \mu_R) = (0.5, 2.0)$ and $(2.0, 0.5)$, are excluded based on PMG recommendations. The envelope of these variations is taken to represent the up and down uncertainties. The PMGSystematicsTool [174] is utilized to combine these variations. For Sherpa 2.2.11 samples (e.g., QCD $W\gamma jj$ and $Z\gamma jj$), the scale variations also include the parton shower component. In this case, the scale is consistently varied for both the parton shower and matrix element, following recommendations in Ref. [175].

6.6.2.2 PDF and α_S uncertainties

Uncertainties in the underlying PDFs used for the Monte Carlo samples stem from experimental uncertainties in the data used for the PDF fits, as well as uncertainties in the functional forms of the fits. These uncertainties are assessed by varying the PDFs. NNPDF30 serves as the nominal PDF set for all samples in this analysis. PDF variations are combined following the guidelines in [176] and [177], using the PMGSystematicsTool. In addition, alternative PDFs (e.g., NNPDF31, CT14, MSHT, PDF4LHC) are compared to the nominal PDF, with their respective uncertainties assessed. If the alternate PDF deviates from the

nominal one and the difference is not covered by the nominal PDF uncertainties, an additional uncertainty is assigned.

For QCD $W\gamma jj$ and QCD $Z\gamma jj$ samples, an additional uncertainty is introduced for the strong coupling constant α_S . Since α_S affects the cross-sections used in the PDF fits, α_S uncertainties are included by evaluating the same PDF set with two different α_S values. This uncertainty is then combined with the PDF uncertainties using the PMG SystematicsTool.

The theoretical variations for the Sherpa signal sample in the signal region used for the neural network fit are illustrated in Figure 6.33. Theoretical systematics are accounted for in all Monte Carlo background estimates.

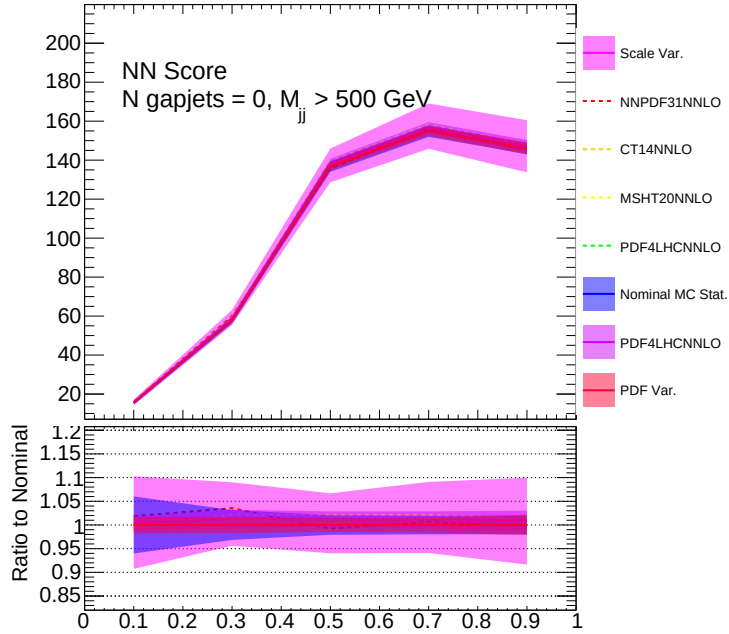


Fig. 6.33: Systematic theory variations, as combined using the PMGSystematicsTool.

6.6.2.3 QCD Generator Choice Uncertainty

A significant discrepancy exists between the QCD background predictions from MadGraph and Sherpa. To account for potential QCD mismodelling, the variation between the predicted shape and yield of $W\gamma jj$ from MadGraph and Sherpa is treated as an uncertainty. Separate nuisance parameters are assigned to the shape and normalization differences. The resulting nuisance parameters are displayed in 6.34 for both the signal and control regions.

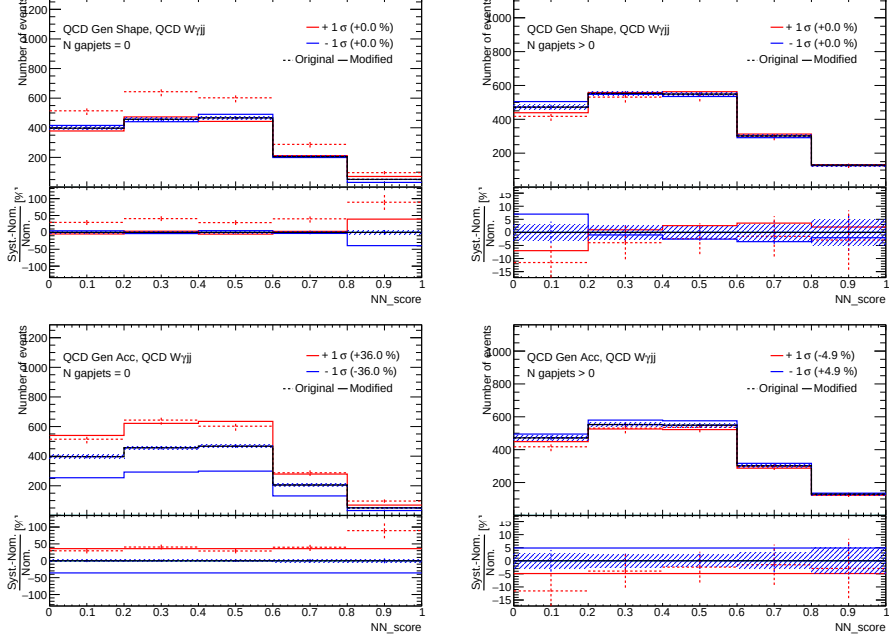


Fig. 6.34: QCD modelling systematics for the shape and normalization differences between MadGraph and Sherpa. The dotted line represents the systematic uncertainty before it is separated into normalization and shape components.

To prevent double counting of jet-related experimental uncertainties, such as jet energy scale and jet flavor uncertainties, Monte Carlo to Monte Carlo calibrations are applied.

6.6.2.4 Electroweak Generator Choice Uncertainty

An additional uncertainty related to the generator choice is included to account for the differences in the signal predictions between MadGraph and Sherpa. Only the shape variation is considered as a systematic uncertainty. The uncertainty due to the electroweak generator choice is illustrated in both the signal and control regions in Figure 6.35.

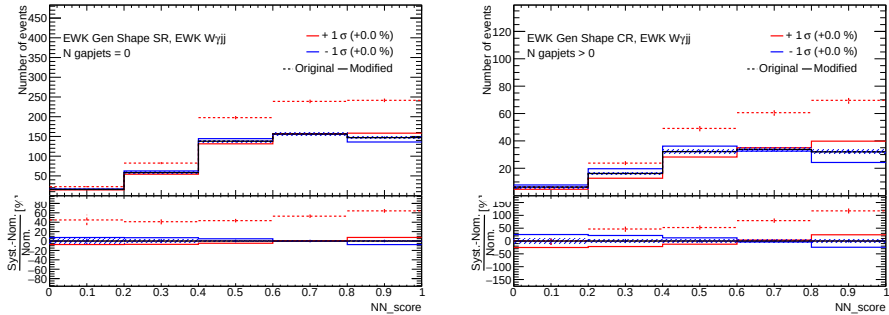


Fig. 6.35: Signal modelling systematic for the shape difference between MadGraph and Sherpa. The dotted line represents the systematic uncertainty before the normalization effect is removed.

6.6.3 Experimental Uncertainties

Experimental uncertainties are evaluated following the latest recommendations from the CP group. For each experimental systematic, the Monte Carlo template is shifted by $\pm 1\sigma$. The key effects considered are:

- Photons: Uncertainties in the ID and isolation efficiency scale factors.
- Electrons: Uncertainties in ID, isolation, reconstruction, and trigger efficiency scale factors.
- Egamma: Uncertainties in energy resolution and scale.
- Muons: Uncertainties in ID, isolation, reconstruction, TTVA, and trigger efficiency scale factors.
- Jets: Uncertainties in energy scale and resolution, η calibration, flavor tagging efficiencies, precision flavor uncertainties, vertex tagging, and b-tagging.
- MET: Uncertainties in the resolution and scale of MET soft tracks.
- PRW: Uncertainties in pileup reweighting scale factors.
- Luminosity

6.6.4 Treatment of Uncertainties in Fit

Each uncertainty source mentioned above is implemented as a nuisance parameter, θ , constrained by a standard Gaussian distribution (mean 0, width 1). A separate nuisance parameter is created for each bin in the fit to account for limited Monte Carlo statistics, with a Poisson constraint applied for the statistical uncertainty. All nuisance parameters are then floated to minimize the negative log-likelihood. A post-fit value of θ significantly different from 0 suggests a preference for a deviation in the uncertainty, while an uncertainty smaller than 1 indicates the data has enough statistical power to constrain that uncertainty.

Experimental uncertainties for the Monte Carlo backgrounds are correlated across processes and regions. PDF and α_S uncertainties are correlated between regions but remain uncorrelated across different processes. Since scale uncertainties are meant to account for missing higher-order terms in the partonic cross-section expansion, they are not treated as correlated between regions.

Normalization uncertainties for the signal theory predictions are excluded from the fit, as the signal normalization is determined from data.

6.7 Results and Fiducial Cross Section

6.7.1 NN Score Fit and Asimov Dataset

To extract the electroweak (EW) contribution, a profile likelihood fit is performed on the neural network (NN) output distribution using TRExFitter. The objective of the fit is to determine the signal strength parameter μ_{EW} , defined as $\mu_{EW} = N_{EW}^{meas}/N_{EW}^{exp}$, where N_{EW}^{meas} and N_{EW}^{exp} represent the observed and expected event counts, respectively. This parameter is fit in both the control region and the signal region, distinguished by the presence of 0 or more than 0 jets in the rapidity gap between the two leading jets.

The normalization of the QCD $l\nu\gamma$ background template is simultaneously fitted in both regions. Other Monte Carlo backgrounds, such as top quark and $ll\gamma$ processes, are incorporated into the fit and are allowed to vary within their respective uncertainties. Data-driven estimates for fake contributions are also included as inputs to the fit.

Two fit strategies are employed, using either the NN output distribution or the rapidity gap $\Delta\eta(jj)$ between the two leading jets as the discriminating variable.

The likelihood function for fitting both the NN distribution and $\Delta\eta(jj)$ is constructed as:

$$L(n|\mu_{ew}, \mu_{qcd}, \theta) = \prod_i Pois(n_i|\nu_i(\mu_{ew}, \mu_{qcd}, \theta)) \prod_k f_k(a_k|\theta_k) \quad (6.20)$$

Here, μ_{EW} represents the parameter of interest (POI), and μ_{QCD} corresponds to the QCD normalization. The terms n_i and v_i denote the observed and expected event counts in bin i , respectively. The measurement incorporates a set of nuisance parameters, θ , which account for the impact of systematic uncertainties on the fit. These uncertainties are included in the fit as constraints of the form $f_k(a_k, \theta_k)$. The fit procedure seeks to minimize a test statistic, specifically the negative log-likelihood, expressed as:

$$NLL(\mu_{EW}, \mu_{\hat{EW}}, \hat{\theta}, \hat{\theta}) = -2 \ln \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})} \quad (6.21)$$

The significance of the measurement is determined by evaluating the negative log-likelihood (NLL) under the background-only hypothesis, where $\mu_{EW} = 0$. The significance is calculated using the following expression:

$$Z_{meas} = \sqrt{NLL(\mu_{EW} = 0)} \quad (6.22)$$

Expected results are derived using an Asimov dataset in the signal region and real data in the control region. The Asimov dataset is constructed by performing a background-only fit to the data in the control region. The fitted QCD normalization factor and nuisance parameters from this fit are then used to generate the Asimov dataset in the signal region. Following this, a signal-plus-background fit is applied to the control region data and the Asimov dataset in the signal region.

Since the pileup background is proportional to real data in each bin, including pileup in the signal region would effectively reveal signal data before unblinding. Therefore, the pileup background template is set to zero in the signal region and will be incorporated after unblinding. The comparison between data and Monte Carlo in the control region, both before and after the control region-only fit used to create the Asimov dataset, is shown in Figure 6.36. The fitted QCD normalization factor is 1.03 ± 0.47 .

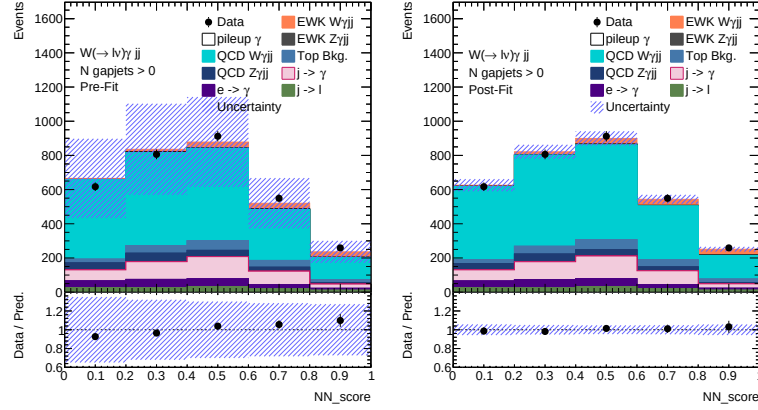


Fig. 6.36: The Control Region-only fit utilized in constructing the Asimov dataset, which is used to report the expected results.

6.7.2 Expected Results

The pre-fit and post-fit distributions in the signal and control regions, based on the Asimov dataset, are displayed in Figure 6.37.

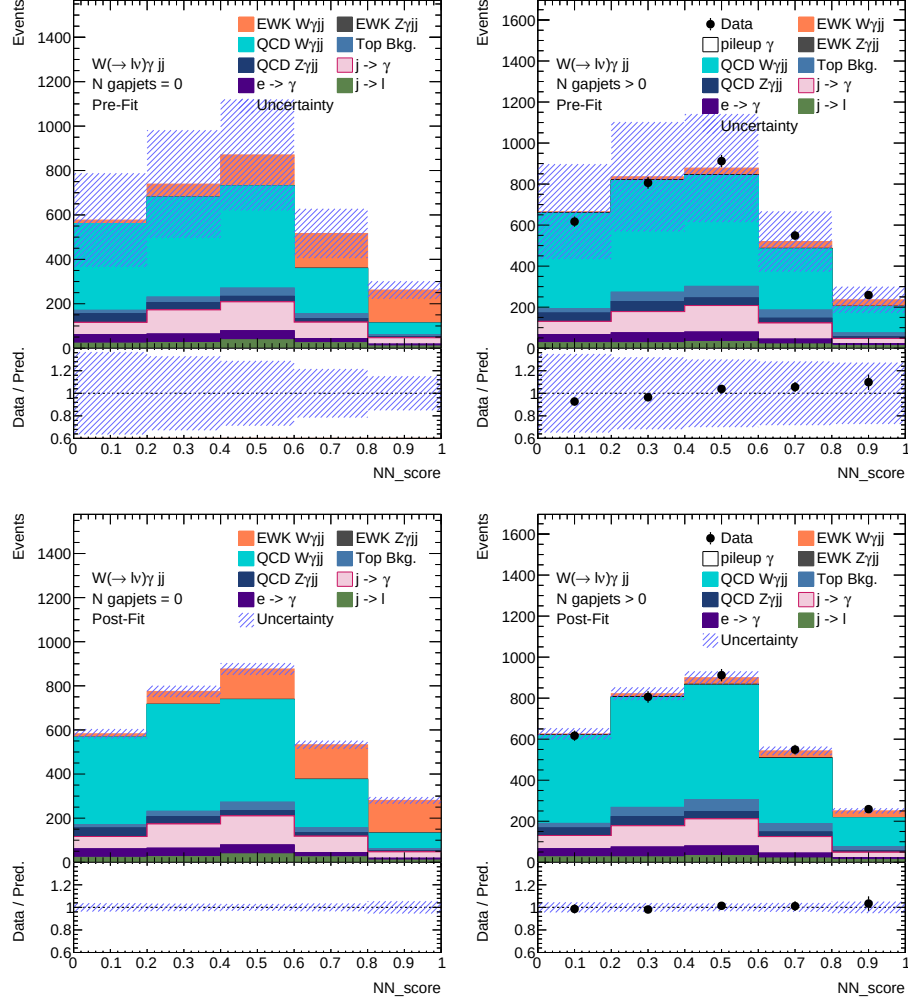


Fig. 6.37: Pre-fit and post-fit plots for the NN score, with uncertainties encompassing all theoretical and systematic uncertainties on Monte Carlo backgrounds and data-driven estimates. The fit is conducted on modified Asimov data in the signal region and actual data in the control region.

The fitted normalization factors are provided in Table 6.20. As anticipated, the signal strength is fitted to 1, while the QCD normalization factor is determined from the background-only fit in the control region.

Table. 6.20: Electroweak signal strength and QCD normalization after the fit to Asimov data.

Parameter	Value
μ_{EW}	$1.00^{+0.17}_{-0.17}$
μ_{QCD}	$1.03^{0.36}_{-0.36}$

All systematic uncertainties discussed in Section 6.6 are incorporated into the fit. The normalization component of the theory uncertainties for the signal sample is excluded, as the signal acceptance is directly fitted to data. Figure A.3 in Ap-

pendix A.2 displays the pulls and constraints on the nuisance parameters related to the systematic uncertainties. The constraining of some nuisance parameters demonstrates the data’s ability to reduce these uncertainties. Overconstrained nuisance parameters likely arise from asymmetric errors associated with the nuisance parameters.

The relative impact of each nuisance parameter is assessed by conducting the fit while fixing each nuisance parameter individually, and then comparing the result to the nominal fit. Figure A.4 in Appendix A.2 presents the relative impact of the systematic and theoretical uncertainties on the parameter of interest.

The expected significance is calculated to be 6.26σ .

6.7.3 Observed Results

Observed results are presented below, using Sherpa as the nominal signal hypothesis. The post-fit observed event yields, along with the signal and control region yields from the data, are provided in Table 6.21.

Table. 6.21: Yields after the fit to data in both the signal and control regions, with Sherpa representing the signal hypothesis.

	Signal Region	Control Region
EWK $W\gamma jj$	776.04 ± 91.00	190.94 ± 40.00
QCD $W\gamma jj$	1628.19 ± 115.71	1896.2 ± 146.56
QCD $Z\gamma jj$	114.78 ± 33.09	147.82 ± 68.62
Top Bkg.	110.11 ± 18.46	189.25 ± 39.07
$j \rightarrow \gamma$	392.34 ± 54.55	412.54 ± 56.48
$e \rightarrow \gamma$	147.58 ± 5.44	172.20 ± 6.12
$j \rightarrow l$	115.72 ± 16.08	113.27 ± 9.86
pileup γ	45.75 ± 0.65	11.18 ± 0.16
EWK $Z\gamma jj$	11.63 ± 1.04	6.65 ± 0.81
Total	3342.12 ± 61.33	3140.04 ± 99.48
Data	3341	3143

The pre-fit and post-fit yields in the signal and control regions are displayed in Figure 6.38. A significant mismodelling of the signal normalization in Sherpa is evident.

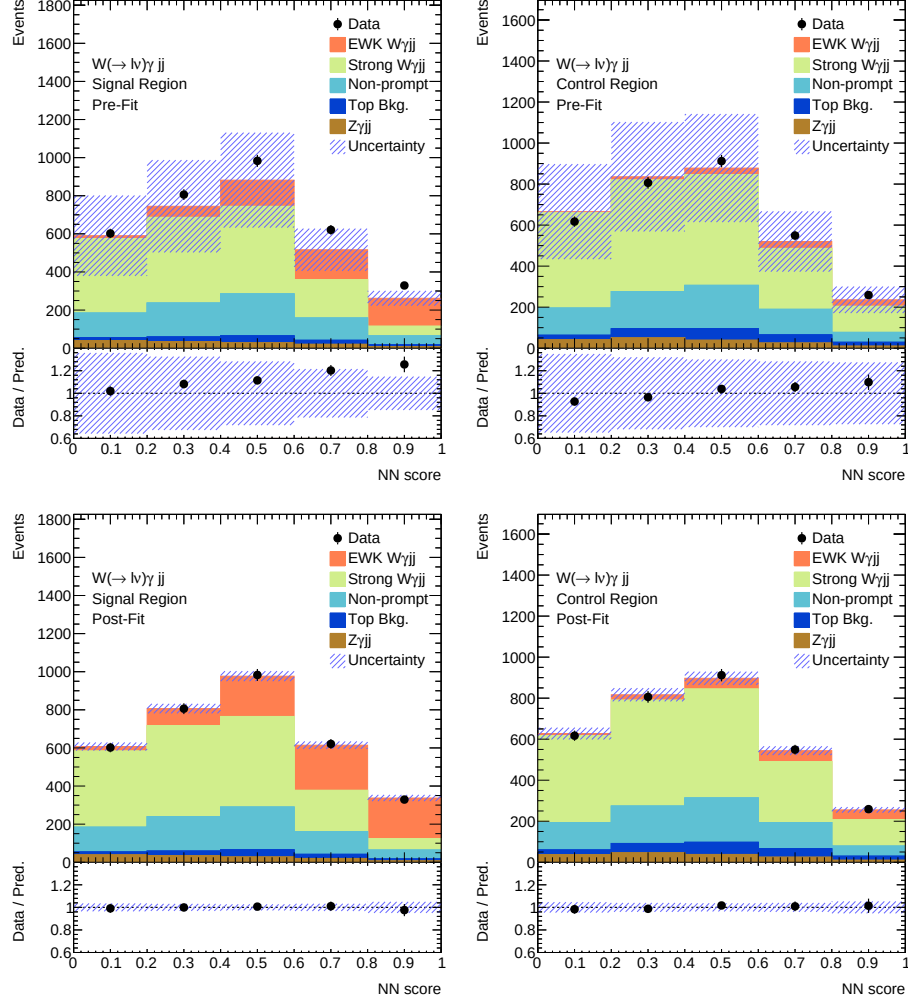


Fig. 6.38: Pre-fit and post-fit NN score plots under the Sherpa signal hypothesis. The uncertainties account for all theoretical and systematic uncertainties on Monte Carlo backgrounds and data-driven estimates. The fit is performed using the full data in the signal region and data from the control region.

The fitted normalization factors are presented in Table 6.22.

Table. 6.22: Electroweak signal strength and QCD normalization after the fit to data, with Sherpa as the signal hypothesis.

Parameter	Value
μ_{EW}	$1.51^{+0.19}_{-0.19}$
μ_{QCD}	$1.01^{+0.36}_{-0.36}$

The pulls of the nuisance parameters are displayed in Figure 6.39.

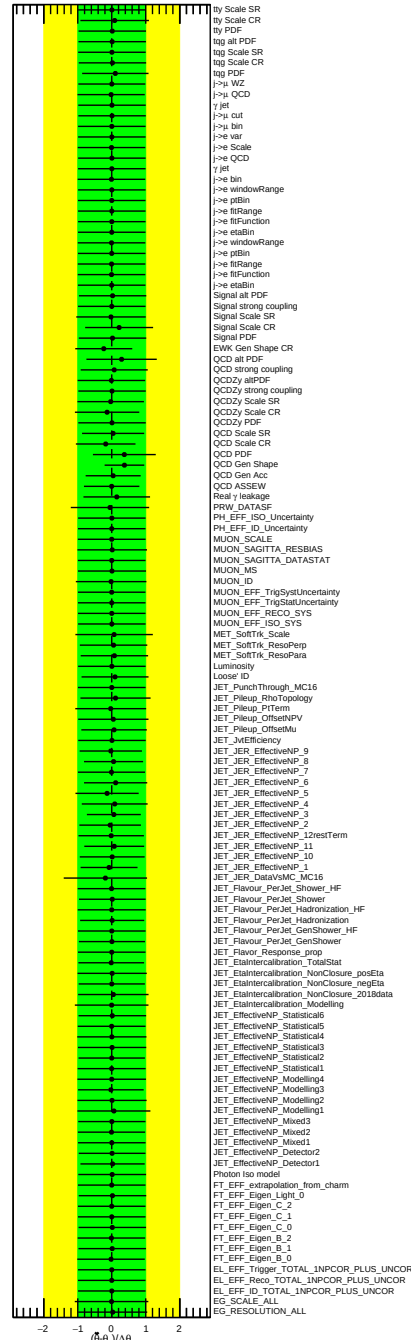


Fig. 6.39: Impact of individual nuisance parameters on the fit to data in both the signal and control regions.

The impact of uncertainties on the parameter of interest is illustrated in Figure 6.40.

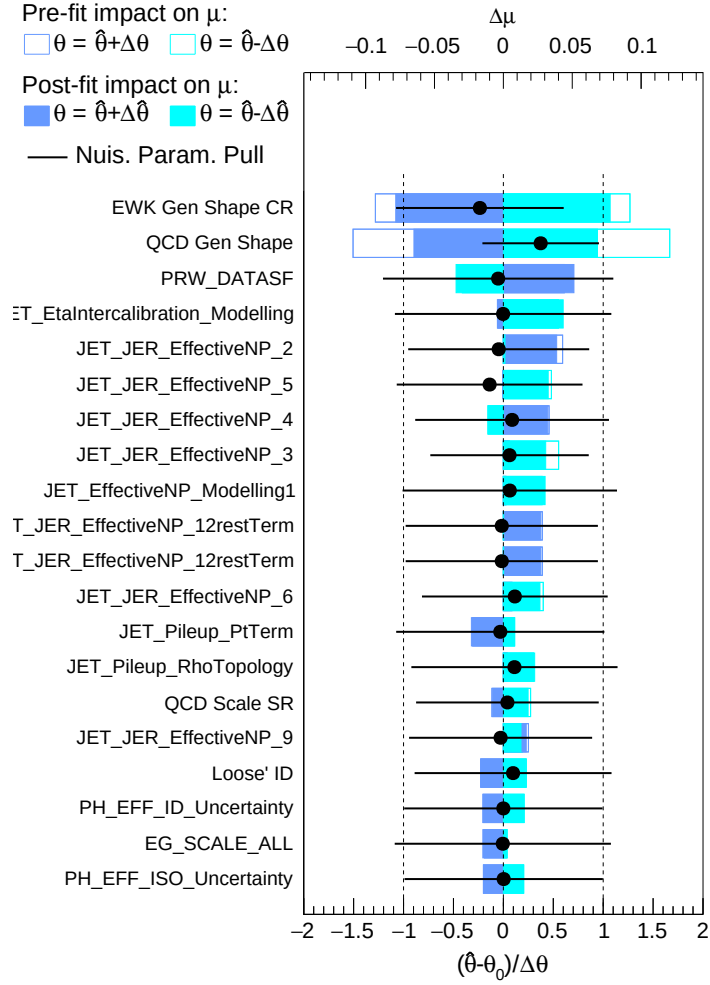


Fig. 6.40: The impact of individual nuisance parameters on the parameter of interest when Sherpa is used as the signal hypothesis.

Figure 6.41 displays the likelihood scan alongside the expected likelihood curves. These scans are utilized to derive both the observed and expected significance values.

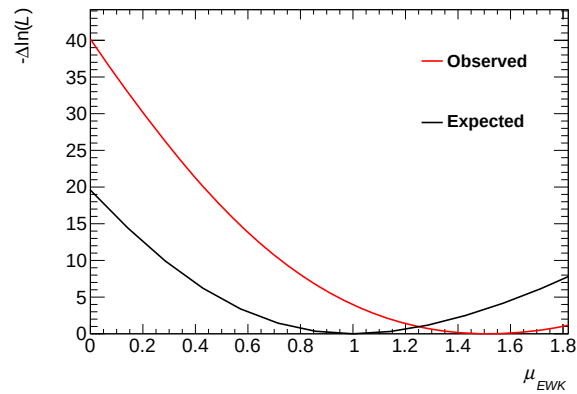


Fig. 6.41: Likelihood scan for the parameter of interest, presented for both expected and observed results, with Sherpa as the signal hypothesis.

The observed significance is 8.96σ , while the expected significance is 6.26σ .

6.7.4 Extraction of Fiducial Cross Section

The fiducial cross section is computed using the following expression:

$$\sigma^{fid} = \frac{\mu \cdot N^{\text{exp}}}{C\mathcal{L}} \quad (6.23)$$

where N^{exp} represents the expected event count in data, μ is the fitted normalization factor for the electroweak signal, $\mathcal{L}$ stands for the dataset's integrated luminosity, and C accounts for detector effects such as reconstruction inefficiencies.

$$C = \frac{N^{\text{reco}}}{N^{\text{fid}}} \quad (6.24)$$

The correction factor C is obtained using the signal Monte Carlo dataset. In this context, N^{reco} refers to the number of reconstructed events passing the selection cuts in both the signal and control regions, whereas N^{fid} corresponds to the truth-level events that meet the fiducial selection requirements. The fiducial cross section is then calculated by applying the correction factor derived from the combination of muon and electron channels. For the Sherpa signal sample, the correction factor is determined to be $C = 0.52 \pm 0.02$ for the combined channels, with $C = 0.55 \pm 0.09$ for the electron channel and $C = 0.49 \pm 0.08$ for the muon channel. The closeness of these values arises from the interplay of a lower electron identification efficiency and a higher trigger efficiency [178], [179], alongside a higher muon identification efficiency with a relatively lower trigger efficiency [180, 181].

The uncertainty in the measured fiducial cross section due to a specific systematic or theoretical uncertainty is computed as follows:

$$\Delta\sigma = \sigma_{\text{nominal}} - \frac{(\mu + \Delta\mu)N^{\text{exp}}}{(C + \Delta C)\mathcal{L}} \quad (6.25)$$

The nominal correction factor C along with the extracted electroweak normalization factor μ are used to calculate the fiducial cross section. Variations in C due to systematic or theoretical uncertainties, denoted ΔC , lead to changes in both N^{reco} and N^{fid} . Similarly, the change in μ , referred to as $\delta\mu$, is derived by refitting the model with the nuisance parameter associated with the uncertainty fixed at $\hat{\theta} \pm \Delta\hat{\theta}$. The interplay between μ , N^{reco} , and N^{fid} ensures that systematic uncertainties affecting $\Delta\mu$ are properly incorporated into the calculation.

It is worth noting that a statistically significant difference exists between the correction factors calculated from the MadGraph and Sherpa samples. For the

MadGraph signal sample, $C = 0.56 \pm 0.03$. In evaluating the uncertainty stemming from the electroweak generator choice, the difference in the correction factor, δC , is computed based on the discrepancy between the MadGraph and Sherpa results. This difference is symmetrized, consistent with the typical approach for handling generator choice uncertainties.

The measured (expected) fiducial cross section is $\sigma^{\text{fid}} = 13.2(8.8) \pm 2.5(2.1)$. The contributions from various uncertainties to the fiducial cross section are detailed in Tables 6.23 and 6.24, which correspond to measured and expected cross-section values, respectively. A comparison of these results with predictions from Sherpa and MadGraph is illustrated in Figure 6.42.

Table. 6.23: Fractional contributions from various uncertainty sources to the measured fiducial cross section.

Uncertainty Source	Fractional Uncertainty
MC Stats.	0.11
Jets	0.08
Lepton,Photon,Pileup	0.08
EW Wgamma jj Model	0.07
Strong Wgamma jj Model	0.06
Non-prompt Background Model	0.02
Luminosity	0.02
Other Background Model	0.02
E_T^{miss}	0.01

Table. 6.24: Fractional uncertainties from different sources contributing to the expected fiducial cross section.

Uncertainty Source	Fractional Uncertainty
MC Stats.	0.15
Strong Wgamma jj Model	0.11
Jets	0.09
EW Wgamma jj Model	0.08
Lepton,Photon,Pileup	0.07
Non-prompt Background Model	0.03
Other Background Model	0.02
Luminosity	0.02
E_T^{miss}	0.01

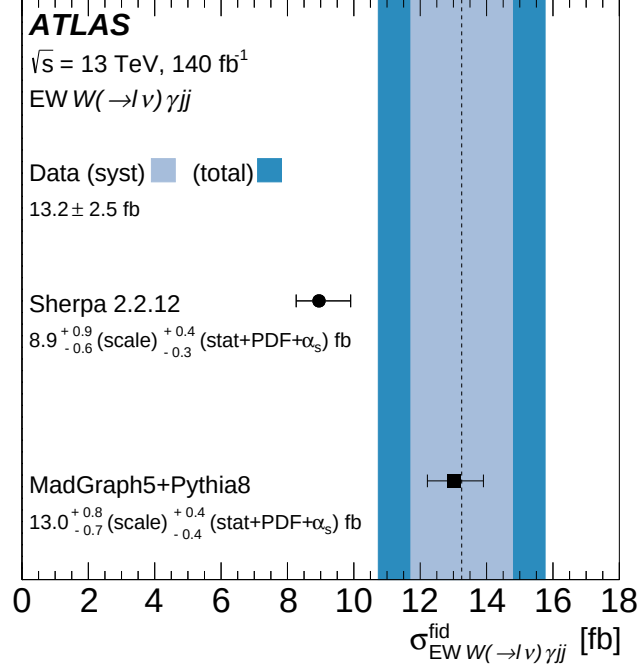


Fig. 6.42: The measured fiducial cross section compared to the predictions from Madgraph and Sherpa.

6.8 Extraction of differential event yields of EW $W\gamma$ production

6.8.1 Signal Extraction methodology

The $\text{EW } W\gamma jj$ event yields are extracted differentially as functions of m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$, utilizing the approach outlined in Ref. [182]. This method leverages both signal and control regions within a binned log-likelihood fit [183, 184], enabling the simultaneous constraint of both the shape and normalization of the *strong* $W\gamma jj$ background. The data are divided into four regions (SR, CR_A, CR_B, and CR_C), according to the selection criteria based on $\xi_{l\gamma}$ and $N_{\text{jets}}^{\text{gap}}$, as defined in Table 6.4.

The binned log-likelihood is given by:

$$\ln \mathcal{L} = - \sum_{r,i} \nu_{ri}^s + \sum_{r,i} N_{ri}^{\text{data}} \ln \nu_{ri}^s,$$

where r represents one of the four regions SR, CR_A, CR_B, and CR_C, and i denotes the bin of the kinematic variable. Here, N_{ri}^{data} is the observed data yield in bin i of region r , while ν_{ri}^s corresponds to the predicted yield, which depends on the s sources of experimental systematic uncertainties.

The fitted number of events in region r and bin i is expressed as:

$$\nu_{ri} = \mu_{EW,i} \nu_{ri}^{EW,MC} + \nu_{ri}^{strong} + \nu_{ri}^{other,bkg}, \quad (6.26)$$

where $\mu_{EW,i}$ represents the signal strength for $EW W\gamma jj$ in bin i , and $\nu_{ri}^{EW,MC}$ and $\nu_{ri}^{other,bkg}$ correspond to the predicted contributions from the $EW W\gamma jj$ process and other reducible background processes, respectively.

The prediction for *strong* $W\gamma jj$ is constrained using the signal-depleted control regions, governed by the following four relations:

$$\begin{aligned} \nu_{CR_A,i}^{strong} &= b_{L,i} \nu_{CR_A,i}^{strong,MC}, & \nu_{CR_B,i}^{strong} &= b_{H,i} \nu_{CR_B,i}^{strong,MC}, \\ \nu_{SR,i}^{strong} &= b_{L,i} c \nu_{SR,i}^{strong,MC}, \text{ and } & \nu_{CR_C,i}^{strong} &= b_{H,i} c \nu_{CR_C,i}^{strong,MC}. \end{aligned} \quad (6.27)$$

The parameters $b_{L,i}$ and $b_{H,i}$ represent sets of bin-dependent free parameters, corresponding to the regions with $\xi_{l\gamma} < 0.35$ and $\xi_{l\gamma} > 0.35$, respectively. The low- $\xi_{l\gamma}$ parameter $b_{L,i}$ is mainly constrained by CR_A , whereas $b_{H,i}$ is constrained by CR_B . These parameters introduce additional flexibility to the predicted *strong* $W\gamma jj$ event yields, allowing for better alignment between the fitted *strong* $W\gamma jj$ yields and the observed data.

To address potential mismodelling across different N_{jets}^{gap} values, a floating parameter c is included to apply a residual correction. This setup is more stable against fit instabilities compared to the two-parameter linear fit used in Ref. [182], particularly due to the limited number of observed data events.

6.8.2 Input simulations

For each bin i , the binned maximum-likelihood fit includes the following free parameters: the signal strength $\mu_{EW,i}$, the floating parameter c , and the corrections $b_{L,i}$ and $b_{H,i}$ to the *strong* $W\gamma jj$ process. This results in a total of $3 \times N_{bins} + 1$ free parameters, constrained by $4 \times N_{bins}$ data points, where N_{bins} corresponds to the number of bins in the measurement of the differential observable.

Alternative predictions for $EW W\gamma jj$ and *strong* $W\gamma jj$ discussed in Section 6.2 are used to evaluate the systematic uncertainties detailed in Section 6.6. The statistical uncertainties from the finite size of data and Monte Carlo samples are determined using the bootstrap method [185], based on 10 000 toy experiments. For each toy experiment, the signal extraction is repeated, with the event yields in each bin of the signal and control regions sampled according to a Poisson distribution. The mean and RMS of the extracted yields from these toy experiments define the central $EW W\gamma jj$ yield and its associated statistical uncertainty. Sys-

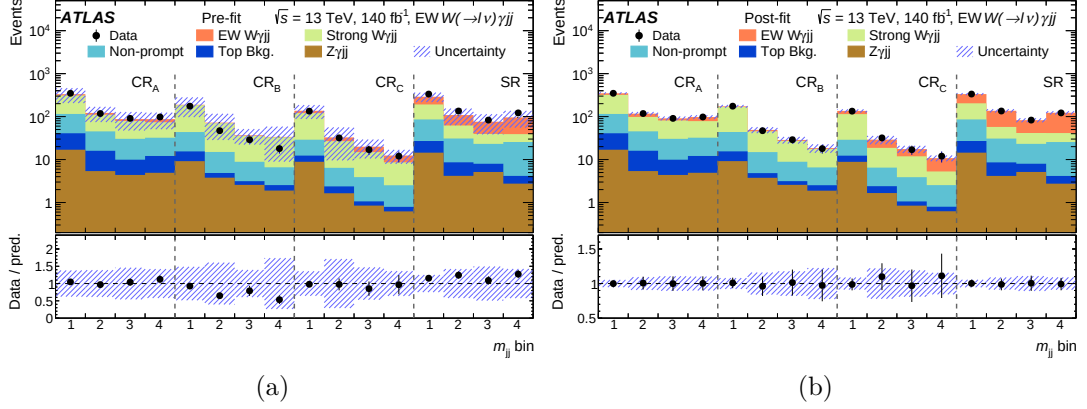


Fig. 6.43: The distribution of observed and predicted yields as a function of m_{jj} in the SR , CR_A , CR_B , and CR_C regions is shown both (a) pre-fit and (b) post-fit. Data points are depicted by solid circles, with the vertical error bars indicating the statistical uncertainty. The predicted yields consist of simulated $EW W\gamma jj$ signal, non-prompt photon and lepton backgrounds estimated using data-driven methods, and other backgrounds determined from simulation. The hashed band represents the quadrature sum of statistical and systematic uncertainties, constrained by the fit. The bin edges are (1, 1.4, 1.7, 2.1, 5.3) TeV.

tematic uncertainties are coherently propagated through the fit by varying each uncertainty source and applying them to the templates across all regions. The theory uncertainties related to QCD scales, PDFs, and α_S are assessed as outlined in Section 6.6.

Figure 6.43 presents the pre- and post-fit comparisons between data and predicted yields as functions of m_{jj} in SR , CR_A , CR_B , and CR_C . The floating parameter c takes values between 1.06 and 1.22, depending on the observable, while the overall scaling factor for *strong* $W\gamma jj$ ($b_{L,i}c$) ranges between 1.07 and 1.39. Post-fit agreement between the predicted yields and data is observed across all regions. Pre-fit systematic uncertainties shown in the figure are estimated following the procedures in Section 6.6. The control regions provide strong constraints on the systematic uncertainties, particularly those associated with *strong* $W\gamma jj$ modelling.

6.8.3 Valiation

The differential $EW W\gamma jj$ signal extraction method is validated using two distinct cross-check procedures. In the first validation, an alternative set of control regions is employed for the *strong* $W\gamma jj$ process as described in Equation 6.27. In this approach, the parameters $b_{L,i}$ and $b_{H,i}$ are used to connect the strong background yields at the same N_{jets}^{gap} values, and are constrained at high $\xi_{l\gamma}$, while the floating parameter c accounts for any residual corrections to address mismod-

elling across $\xi_{l\gamma}$. In the second validation method, the data-driven corrections for *strong* $W\gamma jj$ are derived exclusively from either CR_A or CR_C . The extracted *EW* $W\gamma jj$ yields obtained from both of these cross-check methods are found to be consistent with the nominal results.

6.8.3.1 Uncertainties

6.8.3.2 Statistical uncertainties in the data

To estimate the statistical uncertainty in the data, 10,000 toy distributions are generated from the Asimov dataset. For each toy, the bin contents are sampled from a Poisson distribution with a mean equal to the original bin value. The root mean square (RMS) of the resulting yields, divided by the mean of the toy datasets, is taken as the relative statistical uncertainty, R^{stat} . This relative uncertainty is then multiplied by the central value of the extracted EW yield to obtain the final absolute uncertainty attributed to the data.

$$R^{\text{stat}} = \frac{\text{RMS}_{\text{Data}}(N_{\text{EW, Sherpa}, i})}{\langle N_{\text{EW, Sherpa}, i} \rangle_{\text{Data}}} \quad (6.28)$$

6.8.3.3 MC statistical uncertainties

The statistical uncertainty from the Monte Carlo (MC) is evaluated by generating 10,000 bootstrap replicas of all the MC templates in the signal region (SR) and control regions (CRs). Each bootstrap is a fluctuated replica, sampled according to a unit Poisson distribution, while maintaining correlations between different templates.

Signal extraction is then independently performed for each bootstrap sample. Following the extraction, the relative MC statistical uncertainty is calculated as

$$R_{\text{MC Stats}}^{\text{syst}} = \frac{\text{RMS}_{\text{MC}}(N_{\text{EW, Sherpa}, i})}{N_{\text{EW, Nominal}}} \quad (6.29)$$

where RMS_{QCD} denotes the root mean square (RMS) calculated across all the bootstrap samples in which the QCD- $W\gamma jj$ templates were varied. This RMS provides a measure of the fluctuations in the extracted yields due to the statistical uncertainties in the QCD background templates.

6.8.3.4 Experimental systematic uncertainties

The experimental uncertainties encompass the sources outlined in Section 6.6.3. A comprehensive list is provided below:

- Jet Energy Scale (JES) uncertainties arising from:
 - The EffectiveNP nuisance parameters, which account for uncertainties

related to absolute in-situ calibrations (such as those from γ/Z +jet and multi-jet balance measurements).

- Additional JES uncertainties due to eta intercalibration, pileup, flavor-dependent effects, and uncertainties from punch-through.
- Jet Energy Resolution (JER) uncertainties originating from:
 - The EffectiveNP nuisance parameters, capturing uncertainties associated with the noise term and in-situ calibrations from dijet measurements.
 - Discrepancies between MC-simulated and data-driven JER measurements.
- Energy scale and resolution uncertainties for muons and electrons/photons.
- Systematic uncertainties from pileup reweighting (PRW) and missing transverse energy (MET).

The primary experimental uncertainties stem from JER and JES sources. The signal extraction process is performed using the nominal templates for 1000 bootstraps¹, and also separately using templates corresponding to the experimental systematic nuisance parameters. For each specific nuisance parameter (e.g. “JER_EffectiveNP__1up”), the yields for *strong* $W\gamma jj$, *EW* $W\gamma jj$, and prompt backgrounds are aligned with this nuisance parameter —meaning that the experimental uncertainties are treated as correlated between all samples. The nominal systematic uncertainty for a given systematic variation is determined by calculating the average deviation from the nominal value across all bootstraps, normalized by the average of the nominal bootstraps. The relative experimental uncertainty on the central value of the extracted EW yield is represented as $R_{\text{exp}}^{\text{sys}}$. The extracted EW yield in the SR for bootstrap i , under a systematic variation, is denoted as $N_{\text{EW},i}^{\text{exp}}$, while the extracted EW yield for bootstrap i , under the nominal configuration, is denoted as $N_{\text{EW},i}^{\text{Nom}}$.

$$R_{\text{exp}}^{\text{sys}} = \frac{\langle N_{\text{EW},i}^{\text{Nom}} - N_{\text{EW},i}^{\text{exp}} \rangle}{\langle N_{\text{EW},i}^{\text{Nom}} \rangle}, \quad \Delta R_{\text{exp}}^{\text{sys}} = \frac{\text{RMS}(N_{\text{EW},i}^{\text{Nom}} - N_{\text{EW},i}^{\text{exp}})}{\langle N_{\text{EW},i}^{\text{Nom}} \rangle}. \quad (6.30)$$

The statistical uncertainties on $R_{\text{exp}}^{\text{sys}}$, denoted as $\Delta R_{\text{exp}}^{\text{sys}}$, are evaluated by subtracting the systematic bootstrap values from the corresponding nominal bootstrap values and computing the RMS of the resulting distributions. The systematic

¹Due to computational constraints, the statistical resolution of the systematic uncertainties is determined using 1000 bootstraps rather than 10000, with the generator choice uncertainty being the only exception.

uncertainties are subsequently smoothed using a Linear Gaussian Kernel smoothing algorithm to mitigate statistical fluctuations.

6.8.3.5 Data-driven Background Uncertainties

The uncertainties on the data-driven background estimates, as detailed in Section 6.5, are propagated to the extracted EW yield by directly shifting the background templates in the fit according to the corresponding uncertainty. Statistical uncertainties on these templates are treated similarly to the MC statistical uncertainties in the likelihood, with Poisson constraints constructed to account for these uncertainties. Furthermore, statistical uncertainties are explicitly incorporated as up and down variations when shifting the templates. Unlike the treatment of MC uncertainties, no bootstrapping is applied to the data-driven background uncertainties, and no smoothing is performed on the final uncertainties in the extracted EW yield. Smoothing is avoided in this case, as the absence of bootstrapping to assess statistical significance could lead to oversmoothing of these uncertainties.

6.8.3.6 Generator Choice

The generator choice uncertainty for QCD- $W\gamma jj$, denoted as $R_{\text{Gen Choice}}^{\text{sys}}$, is determined prior to smoothing by extracting the EW yield in the SR for both sets of QCD- $W\gamma jj$ templates over 10000 bootstraps. The difference in the extracted yield is calculated for each corresponding pair of bootstraps, and the mean of these differences is taken across all bootstraps. This value is then converted to a relative uncertainty by dividing by the central value of the extracted yield.

$$R_{\text{Gen Choice}}^{\text{sys}} = \frac{\langle N_{\text{EW},i}^{\text{Nom, Sherpa}} - N_{\text{EW},i}^{\text{Nom, MG5}} \rangle}{\langle N_{\text{EW},i}^{\text{Nom, Sherpa}} \rangle}, \quad (6.31)$$

$$\Delta R_{\text{Gen Choice}}^{\text{sys}} = \frac{\text{RMS}(N_{\text{EW},i}^{\text{Nom, Sherpa}} - N_{\text{EW},i}^{\text{Nom, MG5}})}{\langle N_{\text{EW},i}^{\text{Nom, Sherpa}} \rangle} \quad (6.32)$$

where the index i represents the different bootstraps. Note that, although the index i is used for both Sherpa and MadGraph, these bootstraps are uncorrelated. The statistical uncertainty on $R_{\text{Gen Choice}}^{\text{sys}}$, denoted by $\Delta R_{\text{Gen Choice}}^{\text{sys}}$, is calculated by taking the root mean square (RMS) of the differences for each pair of bootstraps.

6.8.3.7 Other theoretical uncertainties

The theoretical uncertainties include contributions from scale, PDF, and α_s variations, which are evaluated for QCD $Z\gamma$, EWK $W\gamma jj$, and QCD $W\gamma jj$ processes. Additionally, uncertainties from fake estimates, interference between

strong $W\gamma jj$ and *EW* $W\gamma jj$, and the statistical uncertainties of the Monte Carlo simulations are considered.

To assess the scale uncertainties, the signal extraction is performed using the nominal templates for 1000 bootstraps, and separately using templates corresponding to scale systematic variations (with only the EW and QCD $W\gamma jj$ backgrounds being bootstrapped). The nominal systematic uncertainty for a given combination of (μ_F, μ_R) is calculated by averaging the deviation from the nominal for each bootstrap and dividing by the average of all nominal bootstraps, as follows:

$$R_{(\mu_F, \mu_R)}^{\text{sys}} = \frac{\langle N_{\text{EW},i}^{\text{Nom}} - N_{\text{EW},i}^{(\mu_F, \mu_R)} \rangle}{\langle N_{\text{EW},i}^{\text{Nom}} \rangle}. \quad (6.33)$$

After fitting each bootstrap, the systematic uncertainties are subsequently smoothed.

For the PDF uncertainties, the signal extraction is performed for 100 different PDF variations per sample, and the RMS of the extracted yields is taken for each bin as the final uncertainty associated with PDF selection. The α_s uncertainties are computed by subtracting the extracted yield from the up variation and the down variation, then dividing the difference by 2. All other systematic uncertainties with both up and down variations are symmetrized similarly by subtracting the down variation from the up variation and dividing the result by 2. It is important to note that all systematics are symmetrized prior to the unfolding procedure.

The uncertainty arising from the interference between *strong* $W\gamma jj$ and *EW* $W\gamma jj$ is determined by comparing the extracted N_{EW} value from an Asimov dataset that includes the interference term with the nominal value, $N_{\text{EW, Nominal}}$, which excludes the interference contribution.

6.8.4 Results

The relative systematic uncertainty values and the final extracted yields based on data are displayed in Figure 6.44 and Figure 6.45.

6.9 Unfolding Results

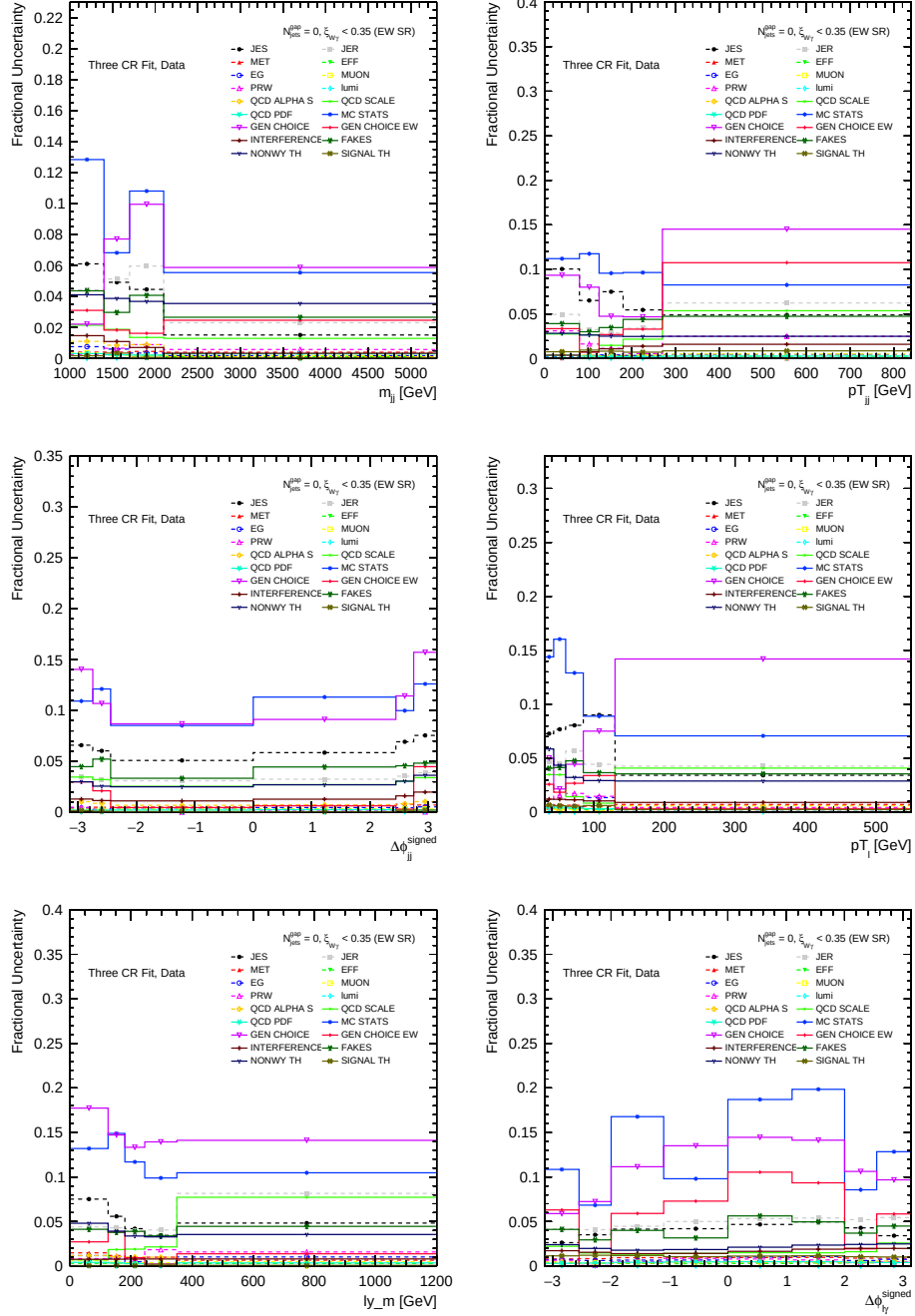


Fig. 6.44: Relative systematic uncertainty values on the extracted electroweak (EW) yield for the data.

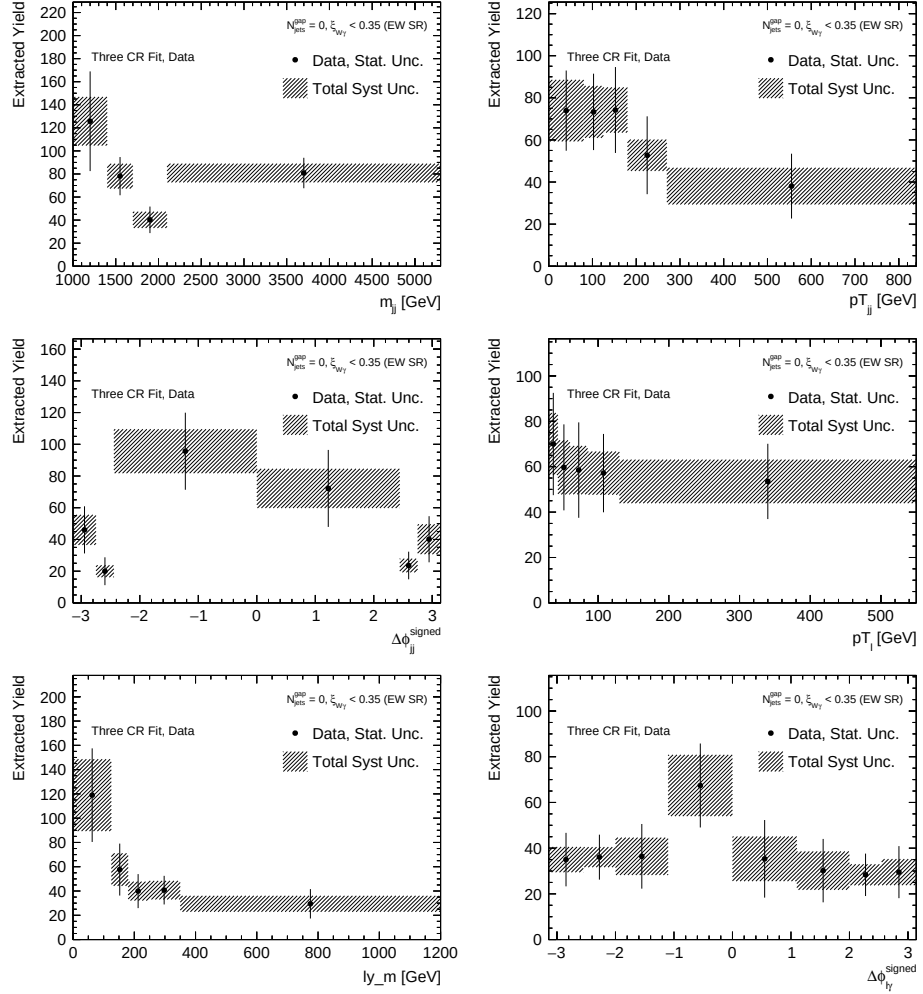


Fig. 6.45: The extracted electroweak (EW) yield for data, including combined systematic uncertainty bands.

The distributions of physical observables are often affected by detector effects such as inefficiencies, acceptance limitations, and finite detector resolution. These distortions must be corrected to recover the true underlying distribution of the observables. One of the objectives in experimental physics is to reconstruct the true distributions from measured data. Unfolding is the procedure that allows for the correction of these detector effects, enabling the determination of truth-level spectra from the observed measurements.

In this analysis, the signal distributions extracted as described in Section 6.8 are unfolded to estimate the corresponding truth-level distributions. The unfolding is performed only in the signal region (SR), which is defined in Section 6.8 and corresponds to the fiducial region outlined in Section 6.3.6 with the additional requirements of $m_{jj} > 1$ TeV and $N_{\text{jets}}^{\text{gap}} = 0$, $\xi_{l\gamma} < 0.35$.

6.9.1 Iterative Bayesian Unfolding

The iterative Bayesian unfolding method, as outlined in Ref. [186], is employed for the unfolding procedure. In this method, the true distribution $\mathbf{x}$ is inferred from the measured distribution $\mathbf{y}$, accounting for the distortions caused by detector effects, represented by the response matrix $\mathbf{A}$. The relationship between these quantities can be expressed as:

$$\mathbf{A} \cdot \mathbf{x} = \mathbf{y} \quad (6.34)$$

The matrix $\mathbf{A}$, commonly referred to as the response or smearing matrix, encapsulates the detector’s behavior, mapping the “true” distribution to the measured one. The primary goal of unfolding is to solve the equation 6.34 and recover the true distribution $\mathbf{x}$ from the known measured distribution $\mathbf{y}$. However, directly inverting the smearing matrix is often impractical, as the matrix may not always be invertible, and the concept of matrix inversion is fundamentally flawed in this context, as discussed by D’Agostini [187].

The relationship between the measured and true distributions can be written explicitly as a summation:

$$t_i = \sum_j P(T_i|M_j)m_j = \sum_j \theta_{ij}m_j \quad (6.35)$$

In this formulation, $P(T_i|M_j)$ and θ_{ij} denote the probability of assigning an event to bin j in the measured distribution given that it originates from bin i in the true distribution. Here, m_j represents the likelihood of observing an event in bin j of the measured distribution, while t_i describes the probability of finding an event in bin i of the true distribution.

Bayesian unfolding utilizes Bayes' theorem to provide a structured approach to estimate the true distribution:

$$\theta_{ij} = P(T_i|M_j) = \frac{P(M_j|T_i) \cdot P(T_i)}{\sum_i P(M_j|T_i) \cdot P(T_i)} = \frac{a_{ji} \cdot P(T_i)}{\sum_i P(M_j|T_i) \cdot P(T_i)} \quad (6.36)$$

In this context, $a_{ji} = P(M_j|T_i)$ refers to the element of the response matrix defined in Equation (6.36), while $P(T_i)$ represents the prior probability for bin i in the true distribution. Within the Bayesian unfolding method, $P(T_i)$ is understood as the prior distribution for the truth-level events.

In Equation (6.36), the response matrix is constructed using Monte Carlo simulated events, where both truth-level and reconstruction-level selections are applied. However, not every event that satisfies the reconstruction-level criteria will contribute to the response matrix; some events passing the reconstruction-level selection may fail the truth-level selection, and vice versa. Therefore, a fiducial correction must be applied to the reconstructed-level distribution before it is passed into the unfolding matrix. Similarly, an efficiency correction must be applied to the truth-level distribution.

After applying fiducial corrections to the Asimov extracted yields from the signal extraction section, the reconstructed-level distribution m_j is propagated through the unfolding formula. However, unfolding performed in this manner may introduce a significant bias based on the initial prior distribution. To mitigate this bias, the unfolding process can be iteratively applied to the data distribution. In each iteration, the result from the previous round is used as the prior input for the subsequent round. The iterative process is expressed as follows:

$$t_{i,n} = \sum \frac{a_{ji} \cdot P(t_{i,n-1})}{\sum_i P(M_j|t_{i,n-1}) \cdot P(t_{i,n-1})} \cdot m_j; n \geq 1; t_{i,0} := T_i \quad (6.37)$$

In this formula, $t_{i,n}$ represents the probability of an event being found in bin i of the truth-level distribution after n iterations. The initial distribution, $t_{i,0}$, is set as the truth-level distribution T_i derived from Monte Carlo simulations.

As the number of iterations increases, the bias introduced by the prior probability distribution is reduced. However, with more iterations, statistical fluctuations become more prominent. Typically, the optimal number of iterations is determined by balancing these two factors, and in most cases, fewer than 10 iterations are sufficient. In this analysis, two iterations are selected for each unfolding procedure to achieve this balance.

6.9.2 Inputs for iterative Bayesian unfolding

The Asimov yields extracted from the electroweak MC distribution, as outlined in the signal extraction section, are used as input for the unfolding procedure. The response matrix for the unfolding is constructed using Sherpa electroweak MC samples. Unfolding is applied in the signal region for all relevant variables, including m_{jj} , p_T^{jj} , and $\Delta\phi_{jj}$. The signal region is defined by the criteria ($N_{jets}^{gap} = 0, \xi_{W\gamma} < 0.35$), with events selected according to the baseline selections specified in the event selection section.

The response matrices, shown in Figure 6.46, are generated by requiring events to pass both truth-level and reconstructed-level selections. The response matrix for $\Delta\phi_{jj}$ is symmetrized by averaging the four corresponding entries for each truth-reco pair. The response matrices indicate a primarily diagonal correlation between the reconstructed distributions and the truth-level distributions, highlighting good agreement between these two stages.

As discussed in Section 6.9.1, not all events passing the reconstructed-level selections contribute to the unfolding matrix. Prior to performing the iterative unfolding, a fiducial correction must be applied to the reconstructed-level distribution. Similarly, an efficiency correction is applied to the truth-level distributions after unfolding, which is automatically handled by the RooUnfold package. Figure 6.47 presents the fiducial correction factors, which are obtained by dividing the projected distribution of the response matrix by the reconstructed-level MC distribution. The fiducial correction factors are consistently above 60%.

6.9.3 Closure tests

In this analysis, three types of closure tests are performed.

The technical closure test is crucial for verifying whether the framework functions as expected. In this test, the distribution from electroweak signal MC samples is used as input to the unfolding process instead of real data collected by the detector. The performance is assessed by comparing the unfolded distribution to the truth-level MC distribution. If the reconstructed distribution originates from the same signal prediction, the unfolding process should exactly reproduce the truth-level distribution.

A closure test addressing MC shape effects is conducted by comparing unfolding results using an alternative signal sample generated with Sherpa. This test, sometimes referred to as a hidden variable test, accounts for effects not included in the CP detector simulation uncertainties. It is performed by unfolding the results using an alternative MadGraph sample, providing a cross-check for generator choice uncertainties, where MadGraph Asimov-extracted yields are unfolded using

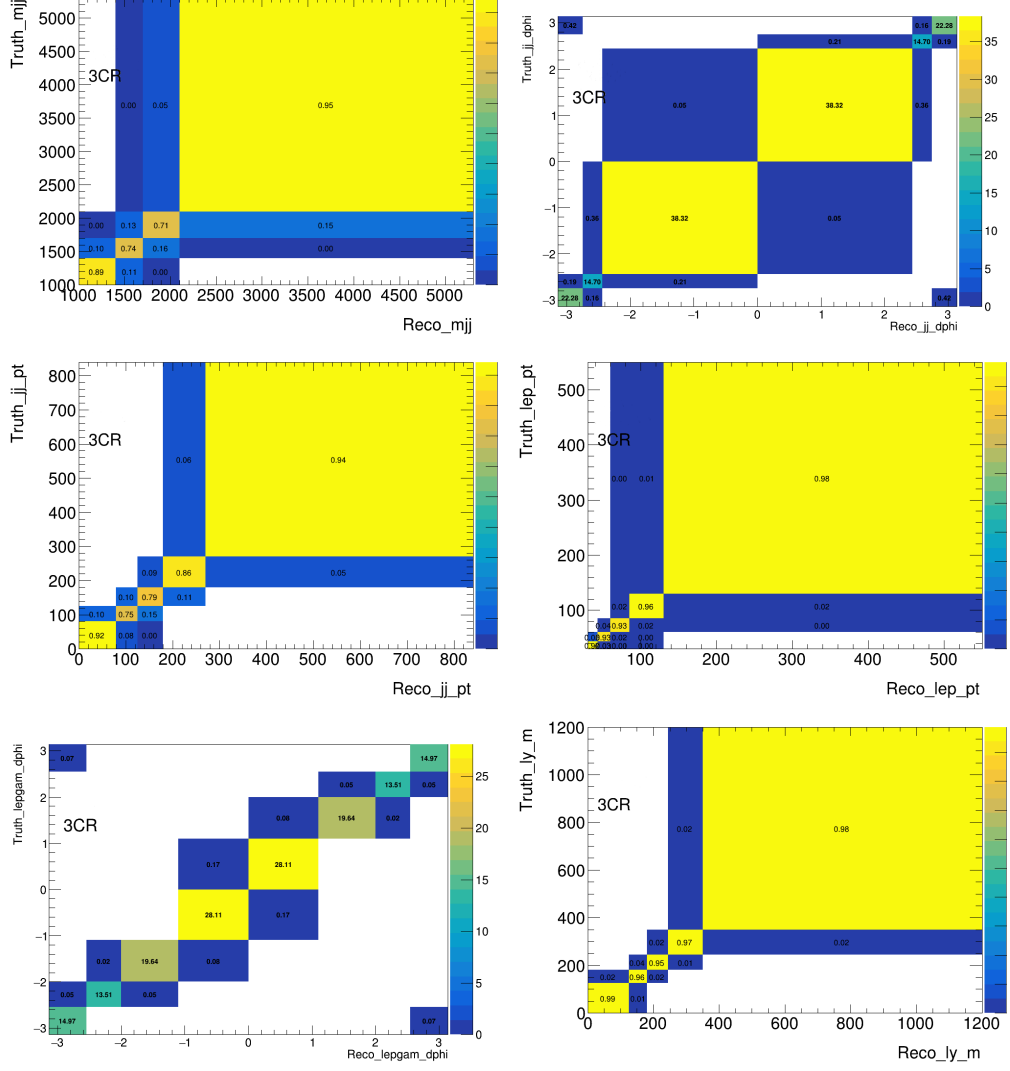


Fig. 6.46: Response matrices for m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$ in SR selections. The combined electroweak signal samples from both the electron and muon channels are used to construct the migration matrices.

the MadGraph response matrix.

The data-driven closure test is designed to evaluate the bias introduced by the unfolding procedure. This test will be applied after unblinding and will serve as a cross-check to avoid double-counting uncertainties in the bias test. The EW $W\gamma$ MC distribution is reweighted to match the data, and the comparison is made between the unfolded distribution and the reweighted truth-level distribution.

6.9.4 Statistical and systematic uncertainties

6.9.4.1 Statistical Uncertainty

Statistical uncertainties are propagated through the EW signal extraction process using the bootstrap method, as outlined in the signal extraction section.

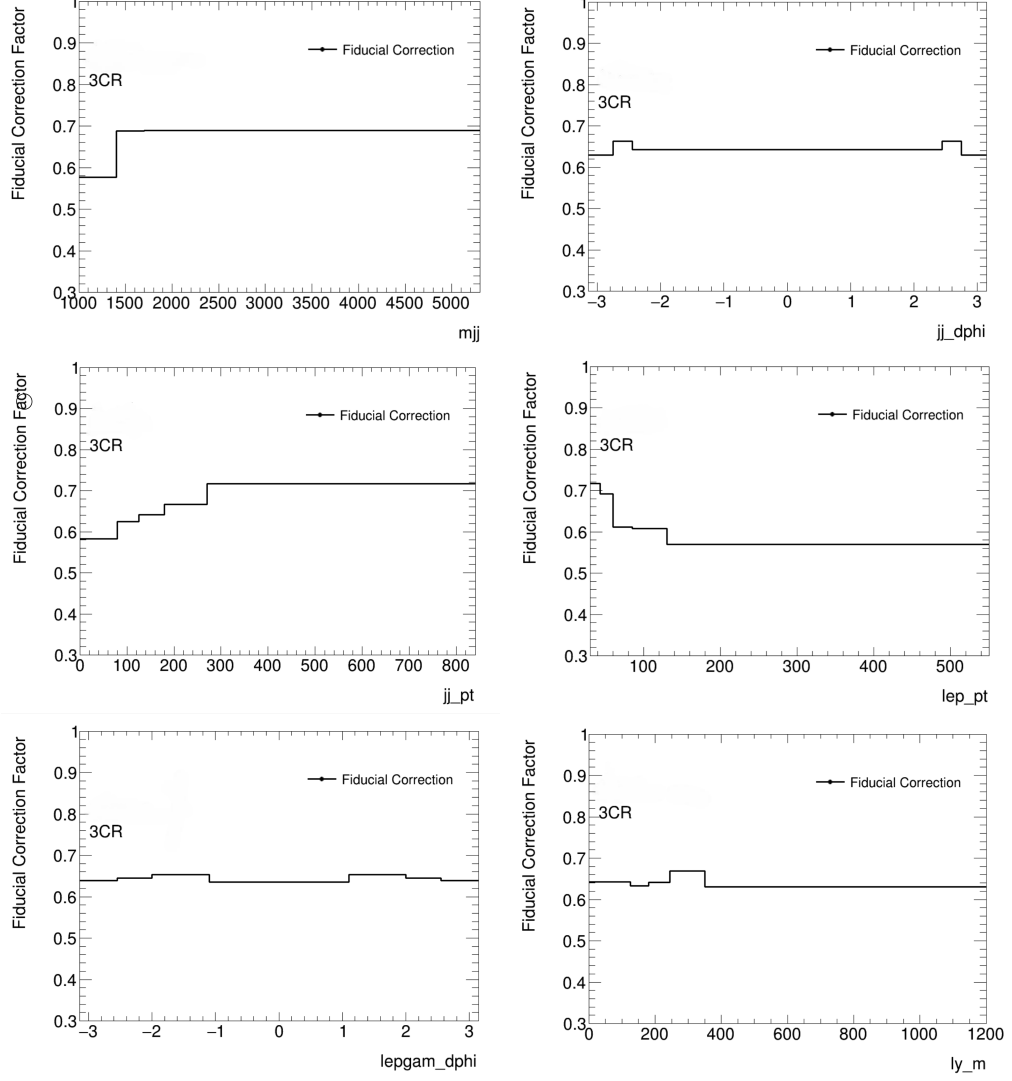


Fig. 6.47: Fiducial correction factors for the nominal unfolding procedure applied to m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$ within the SR selections.

For each statistical variation, 10,000 bootstrap samples are generated. The statistical uncertainty is then estimated using these bootstrap toys, with the mean and RMS values of each bin calculated after the unfolding procedure.

The statistical uncertainties for both the Monte Carlo and Asimov datasets are evaluated via the bootstrap method. As described in the signal extraction section, 10,000 bootstrap toys are generated for each component in the MC (EW, QCD, Non- $W\gamma$, Fakes) and for the Asimov dataset. An example of the unfolded bootstraps for m_{jj} is presented.

The iterative Bayesian unfolding is performed for each of the 10,000 bootstrap samples corresponding to the EW, QCD, Non- $W\gamma$, Fakes, and Asimov datasets. The RMS of the unfolded values in each bin is used to estimate the uncertainty. Figure 6.48 shows the corresponding examples of the relative statistical uncertainties for the EW, QCD, Non- $W\gamma$, Fakes, and Asimov data distributions in m_{jj} .

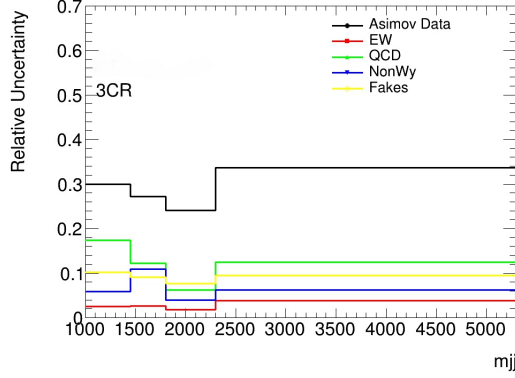


Fig. 6.48: Statistical uncertainties for m_{jj} in the combined electron and muon channels after SR selections and unfolding, based on full Run II Asimov data. Results for the 3CR fit are presented.

6.9.4.2 Experimental Uncertainty

Experimental uncertainties are evaluated by unfolding the extracted EW yields under various systematic uncertainties. The sources of systematics considered in this analysis are detailed in Section 6.6. For each source of systematic uncertainty, a corresponding shift is applied to the Monte Carlo templates. Response matrices and fiducial correction factors are then derived from the Sherpa+Pythia8 electroweak MC samples after applying the same systematic shifts.

6.9.4.3 Theory Uncertainty

As outlined in the theory uncertainties section, each Monte Carlo sample accounts for at least two distinct sources of systematic uncertainty: those arising from the omission of higher-order terms in the cross-section calculation, and uncertainties related to the PDFs utilized in the Monte Carlo generation.

Scale variations are employed to assess the impact of missing higher-order terms in the perturbative expansion of the partonic cross section. For every Monte Carlo sample, six scale variations are applied, while off-diagonal variations are excluded from consideration.

6.9.4.4 Unfolding results

The unblinded unfolded yields and the differential unfolded distributions for the electroweak components within the signal region are obtained. The final results, including the fractional systematic uncertainties and the unfolded differential cross-section distributions, are depicted in Figure 6.49 and Figure 6.50.

6.10 Effective Field Theory Interpretation

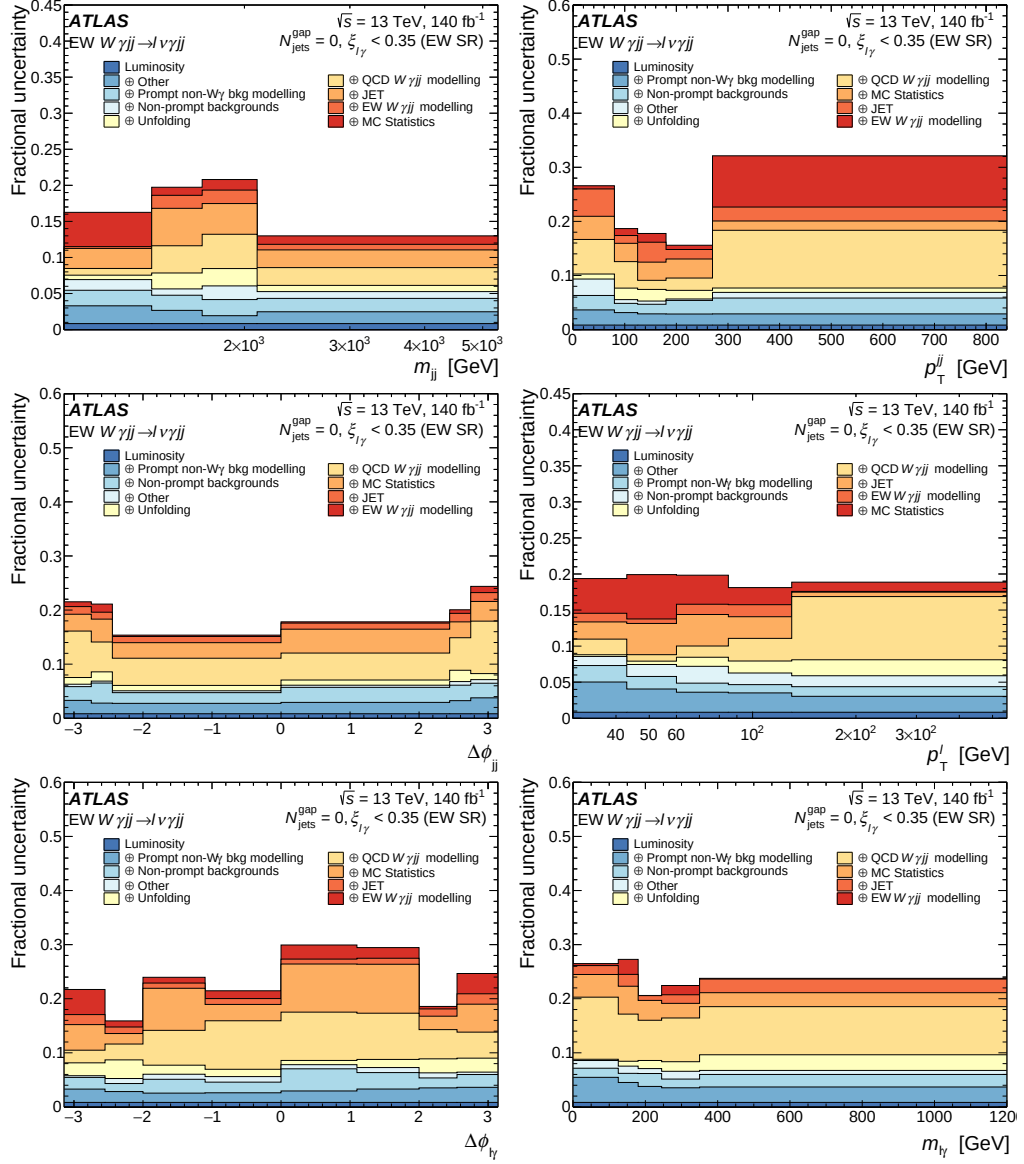


Fig. 6.49: The fractional systematic uncertainties on the unfolded differential cross-sections, obtained from the data, are presented.

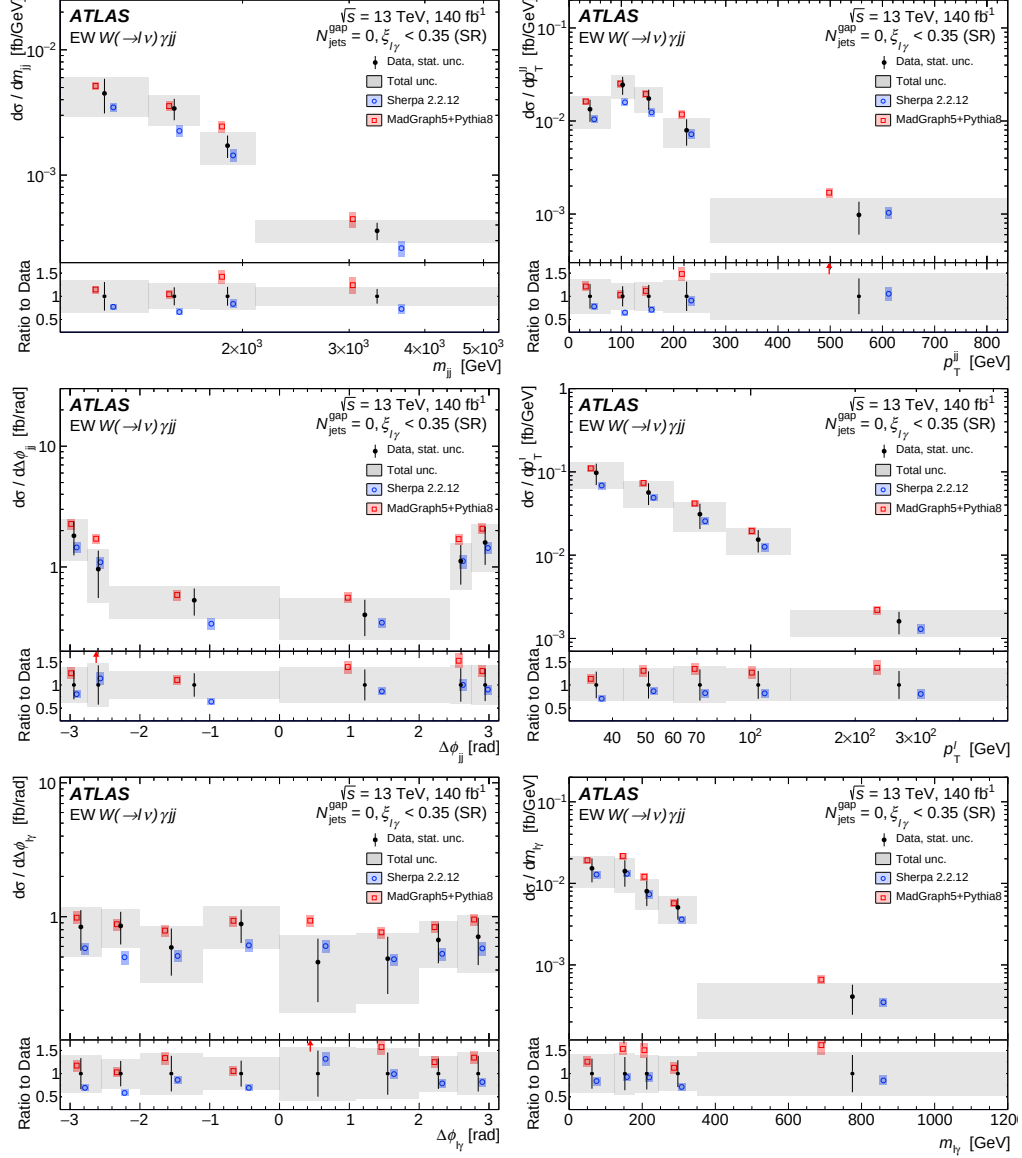


Fig. 6.50: The unfolded differential cross-section distributions for electroweak $W\gamma jj$ in terms of m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$ are shown for the combined electron and muon channels after SR selections and the unfolding process. Truth predictions from Madgraph and Sherpa signal samples are included. Error bars on the predictions account for uncertainties arising from scale variations, PDFs, α_s (for Sherpa), and MC statistical uncertainties.

6.10.1 Introduction

The interactions among gauge bosons are strictly governed by the $SU(2) \times U(1)$ symmetry of the electroweak sector within the Standard Model (SM). Any discrepancies observed between measured cross sections and SM predictions can be indicative of the existence of physics beyond the Standard Model (BSM).

To study these deviations in a model-independent manner, effective field theory (EFT) provides a powerful framework. EFT expands the SM Lagrangian to include higher-dimensional operators, while respecting Lorentz and gauge invariance:

$$\mathcal{L}_{SMEFT} = \mathcal{L}_{SM} + \sum_{n=5}^{\infty} \frac{f_n}{\Lambda^{n-4}} \mathcal{O}_n \quad (6.38)$$

In this formalism, f_n represent the coupling coefficients, $\mathcal{O}_n$ denote the dimension- n operators (with $n > 4$), and Λ corresponds to the energy scale at which new physics could potentially emerge. Although no new particles explicitly appear in this approach, their effects are encoded within these higher-order operators, leading to possible modifications of SM couplings. The constants f_n can be derived from a more fundamental high-energy theory, and therefore, setting limits on f_n imposes indirect constraints on prospective BSM scenarios. It is crucial to note that this effective field theory (EFT) expansion remains valid only below the energy threshold Λ , where the direct effects of new physics are beyond reach. In the SM framework, this energy scale typically aligns with the electroweak vacuum expectation value (v.e.v.).

The lowest-order contributions to quartic gauge boson interactions arise from dimension-8 operators. Table 6.25 outlines the 18 dimension-8 operators, along with their corresponding quartic gauge boson couplings. The measurement is particularly sensitive to the $WW\gamma\gamma$ and $WW\gamma Z$ interactions, both of which appear at tree level within the SM.

The labels S, O, and M correspond to scalar-like, tensor-like, and mixed scalar-tensor operators, respectively. In the scope of this analysis, only tensor-like and mixed operators contribute to the gauge boson couplings of interest. These

Table. 6.25: Dimension-8 operators and their influence on quartic vertices [33].

	WWWW	WWZZ	WW γ Z	WW $\gamma\gamma$	ZZZZ	ZZZ γ	ZZ $\gamma\gamma$	Z $\gamma\gamma\gamma$	$\gamma\gamma\gamma\gamma$
$O_{S,0}, O_{S,1}$	✓	✓			✓				
$O_{M,0}, O_{M,1}, O_{M,6}, O_{M,7}$	✓	✓	✓	✓	✓	✓	✓		
$O_{M,2}, O_{M,3}, O_{M,4}, O_{M,5}$		✓	✓	✓	✓	✓	✓		
$O_{T,0}, O_{T,1}, O_{T,2}, O_{T,3},$	✓	✓	✓	✓	✓	✓	✓	✓	✓
$O_{T,4}, O_{T,5}, O_{T,6}, O_{T,7}$		✓	✓	✓	✓	✓	✓	✓	✓
$O_{T,8}, O_{T,9}$					✓	✓	✓	✓	✓

relevant operators are parameterised in the following manner:

$$\mathcal{O}_{M0} = Tr[W_{\mu\nu}W^{\mu\nu}] \times [(D_\beta\phi)^\dagger D^\beta\phi] \quad (6.39)$$

$$\mathcal{O}_{M1} = Tr[W_{\mu\nu}W^{\mu\beta}] \times [(D_\beta\phi)^\dagger D^\mu\phi] \quad (6.40)$$

$$\mathcal{O}_{M2} = Tr[B_{\mu\nu}B^{\mu\nu}] \times [(D_\beta\phi)^\dagger D^\beta\phi] \quad (6.41)$$

$$\mathcal{O}_{M3} = Tr[B_{\mu\nu}B^{\mu\beta}] \times [(D_\beta\phi)^\dagger D^\mu\phi] \quad (6.42)$$

$$\mathcal{O}_{M4} = [(D_\mu\phi)^\dagger W_{\beta\nu}D^\mu\phi] \times B^{\beta\nu} \quad (6.43)$$

$$\mathcal{O}_{M5} = [(D_\mu\phi)^\dagger W_{\beta\nu}D^\nu\phi] \times B^{\beta\mu} \quad (6.44)$$

$$\mathcal{O}_{M7} = [(D_\mu\phi)^\dagger W_{\beta\nu}W^{\beta\nu}D^\mu\phi] \quad (6.45)$$

$$\mathcal{O}_{T0} = Tr[W_{\mu\nu}W^{\mu\nu}] \times Tr[W_{\alpha\beta}W^{\alpha\beta}] \quad (6.46)$$

$$\mathcal{O}_{T1} = Tr[W_{\alpha\nu}W^{\mu\beta}] \times Tr[W_{\mu\beta}W^{\alpha\nu}] \quad (6.47)$$

$$\mathcal{O}_{T2} = Tr[W_{\alpha\mu}W^{\mu\beta}] \times Tr[W_{\beta\nu}W^{\nu\alpha}] \quad (6.48)$$

$$\mathcal{O}_{T3} = Tr[W_{\mu\nu}W_{\alpha\beta}] \times Tr[W^{\alpha\nu}W^{\mu\beta}] \quad (6.49)$$

$$\mathcal{O}_{T4} = Tr[W_{\mu\nu}W_{\alpha\beta}] \times B^{\alpha\nu}B^{\nu\beta} \quad (6.50)$$

$$\mathcal{O}_{T5} = Tr[W_{\mu\nu}W^{\mu\nu}] \times B_{\alpha\beta}B^{\alpha\beta} \quad (6.51)$$

$$\mathcal{O}_{T6} = Tr[W_{\alpha\nu}W^{\mu\beta}] \times B_{\mu\beta}B^{\alpha\nu} \quad (6.52)$$

$$\mathcal{O}_{T7} = Tr[W_{\alpha\mu}W^{\mu\beta}] \times B_{\beta\nu}B^{\nu\alpha} \quad (6.53)$$

In this context, $D^\beta(D_\beta)$ refers to the covariant derivative, W is the field strength tensor associated with the $SU(2)_L$ gauge group, B represents the $U(1)_Y$ field strength, and ϕ denotes the Higgs field.

Operators of dimension 5, 7, and 9 violate lepton and baryon number conservation, thus they are excluded from this analysis. Dimension-6 operators can generate anomalous triple gauge couplings (aTGC), but these couplings are tightly constrained by vector boson fusion studies. In addition, CP-violating operators arise at dimension 6, impacting both QCD and electroweak vertices, which are of interest in this measurement. While dimension-8 operators also include CP-violating terms, no MadGraph model currently exists to simulate such effects for this study.

It is important to note that when a higher-dimensional operator is introduced into the Standard Model Lagrangian, the corresponding matrix element is modified as follows:

$$A = A_{SM} + f_j A_j \quad (6.54)$$

where A_{SM} represents the Standard Model amplitude, and A_j is the amplitude corresponding to the new operator, which enters the Lagrangian with a coupling f_j . It is important to note that the squared amplitude

$$|A|^2 = |A_{SM} + f_j A_j|^2 = |A_{SM}|^2 + f_j \text{Re}(A_{SM} A_j) + f_j^2 |A_j|^2 \quad (6.55)$$

includes both a contribution from the interference between the Standard Model amplitude and the new operator, which scales linearly with f_j , and a contribution from the new operator alone, scaling quadratically with f_j . These two components are referred to as the linear (or interference) term and the quadratic (or EFT-only) term, respectively.

One final point worth noting: linear terms from operators of dimension higher than 8 are suppressed by the same factor as the dimension-8 quadratic terms (Λ^4). Consequently, these linear contributions can be comparable in magnitude to the dimension-8 quadratic terms in affecting the cross section. However, operators of dimensions higher than 8 are not included in current Monte Carlo generators and are therefore not considered in this study.

6.10.2 Event Generation

Monte Carlo samples for the electroweak production of a W boson and a photon, incorporating contributions from the dimension-8 operators listed earlier, are generated using Madgraph and the Eboli model [188]. To avoid the need for generating a large set of Monte Carlo samples for each value of the couplings under study, the linear and quadratic terms are generated separately. This allows each sample to be reweighted by either the coupling value of interest or the square of the coupling, depending on whether the linear or quadratic term is needed to obtain the prediction for a given coupling value. This method also enables independent study of the linear and quadratic contributions. The validity of the decomposition approach is confirmed by generating decomposed samples with a large coupling value and comparing the sum of these samples with a single sample where the Standard Model and EFT contributions are generated simultaneously. This closure test for decomposition is illustrated in Figure 6.51 for the $T0$ operator.

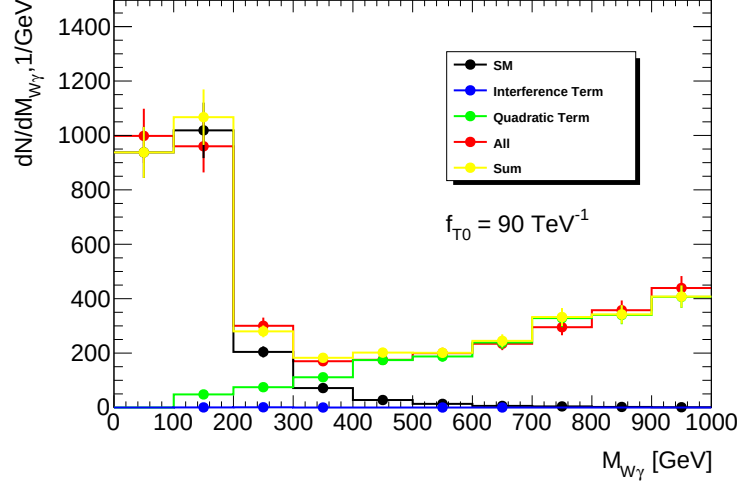


Fig. 6.51: Validation of sample decomposition. “All” refers to a sample generated with both Standard Model and EFT contributions, while “Sum” denotes the total of the individually generated Standard Model, linear, and quadratic terms.

6.10.3 Statistical Model

In this analysis, one-dimensional constraints are placed on each anomalous quartic gauge coupling (aQGC). Specifically, a statistical model is constructed by fitting one aQGC parameter at a time, while all other couplings are fixed to zero. The statistical model for the differential cross section in a given observable X with respect to a coupling c is expressed as follows:

$$\frac{d\sigma^i}{dX}(c) = \frac{d\sigma_{SM}^i}{dX}(1 + \delta\theta) + c \cdot \frac{d\sigma_{int}^i}{dX}(1 + \delta\theta) + c^2 \cdot \frac{d\sigma_{quad}^i}{dX}(1 + \delta\theta) \quad (6.56)$$

where i represents the bin, and σ_{SM} , σ_{int} , and σ_{quad} denote the Monte Carlo predictions for the Standard Model, interference, and quadratic terms, respectively. The term $\delta\theta$ corresponds to a nuisance parameter accounting for uncertainties in both the Standard Model and EFT predictions. The scale uncertainty is treated as a systematic uncertainty affecting both the Standard Model and EFT predictions. Additionally, a nuisance parameter capturing the shape difference between the Madgraph and Sherpa predictions for the Standard Model process is included, impacting only the Standard Model term.

The statistical model described above is fitted to the unfolded data through a maximum likelihood approach, where the likelihood function is defined as:

$$\mathcal{L}(c, \vec{\theta}) = \frac{1}{\sqrt{(2\pi)^k \cdot |V|}} e^{-\frac{1}{2}\chi^2(c, \vec{\theta})} \prod_{\vec{\theta}} \mathcal{G}(\vec{\theta}) \quad (6.57)$$

Here, the χ^2 test statistic quantifies the level of agreement between the statistical model and the unfolded data, and is expressed as

$$\chi^2(c, \vec{\theta}) = [y - f(c, \vec{\theta})]V^{-1}[y - f(c, \vec{\theta})] \quad (6.58)$$

where y represents the unfolded data, $f(c, \vec{\theta})$ is the predicted value, and $\vec{\theta}$ denotes the vector of nuisance parameters. The term $\mathcal{G}(\theta)$ represents a standard Gaussian distribution centered at θ . The variable k corresponds to the number of measurements (in this case, bins), and V refers to the $k \times k$ covariance matrix. The statistical uncertainty from toy simulations is used to construct this covariance matrix. Measurement uncertainties can either be incorporated directly into the covariance matrix or treated as nuisance parameters. When treated as nuisance parameters, this generally leads to slightly more conservative limits, which is the default approach in this analysis.

The likelihood defined above is employed in the construction of a profile likelihood ratio test statistic

$$q(c_x) = -2 \log \frac{\mathcal{L}(c, \hat{\vec{\theta}})}{\mathcal{L}(\hat{c}, \hat{\vec{\theta}})} \quad (6.59)$$

where $\mathcal{L}(c, \hat{\vec{\theta}})$ is the unconditional maximum likelihood, and $\mathcal{L}(\hat{c}, \hat{\vec{\theta}})$ is the maximum likelihood for a fixed value of c .

According to Wilks' theorem, in the asymptotic limit, where the likelihood function converges to a Gaussian form, the test statistic follows a χ^2 distribution with m degrees of freedom, where m represents the number of free parameters in the model. If Wilks' theorem holds, the quantiles of the χ^2 distribution can be used to construct a 95% confidence interval as

$$\int_0^{q(c)} \chi^2(m=1) dq = 95\% \quad (6.60)$$

This procedure is demonstrated by scanning the test statistic as a function of the coupling parameter of interest, specifically for the T0 operator, as shown in Figure 6.52. The coupling values corresponding to a test statistic that falls within the 95% confidence level of the cumulative χ^2 distribution are indicated by a dashed line. The derived 95% confidence interval for this coupling is found to be $[-2.40, 2.44]$.

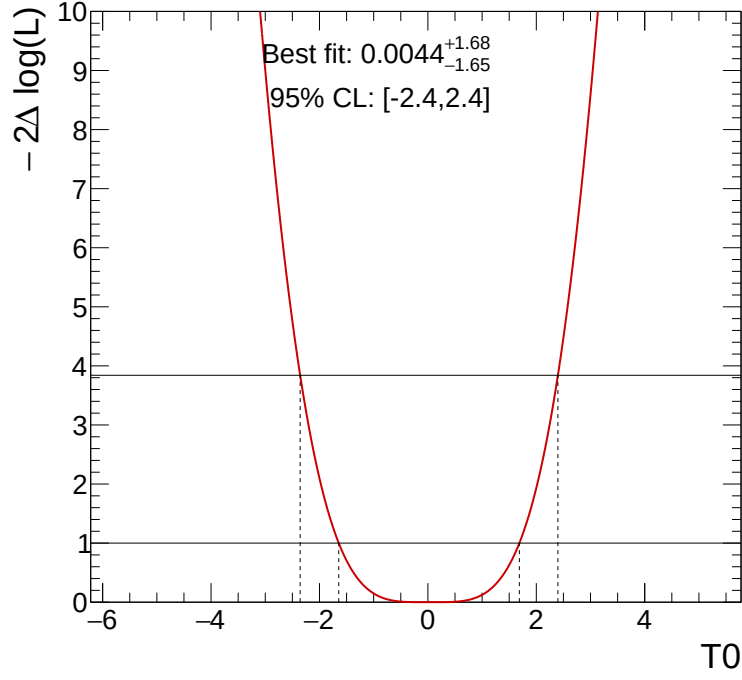


Fig. 6.52: Likelihood scan of the coupling for the T0 operator using a fit of the p_{jj}^T distribution to Asimov data.

The validity of Wilke’s theorem can be assessed through pseudo-experiments, where N toy datasets are generated by fluctuating nuisance parameters and systematic uncertainties around their central values. Both the unconditional and conditional fits are then performed to compute the test statistic. This test statistic should adhere to a χ^2 distribution at the 95% confidence interval boundaries, and any observed deviation helps quantify the extent to which the limits derived from the χ^2 cumulative distribution function either over- or under-cover the true result. Figure 6.53 illustrates the distribution of test statistics from pseudo-experiments when fitting the T0 operator coupling to the p_{jj}^T distribution. At the edges of the 95% confidence interval, it is observed that Wilke’s theorem holds, with the test statistic following the expected χ^2 distribution.

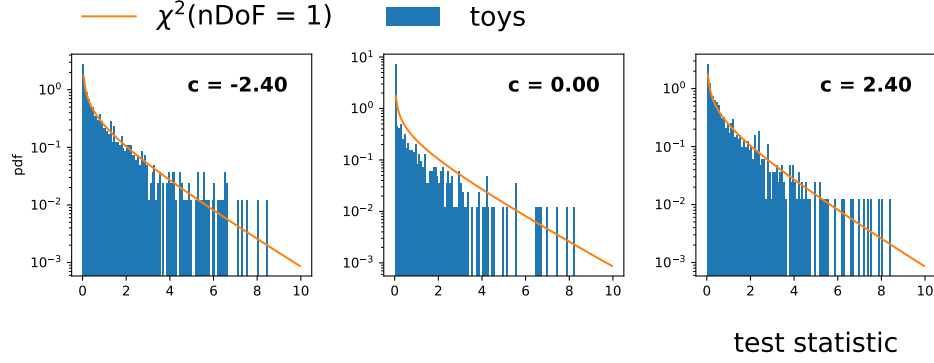


Fig. 6.53: Distribution of test statistics for pseudo experiments at various values of the T0 Wilson coefficient. In the large sample limit, where the likelihood approaches a Gaussian, the test statistic follows a χ^2 distribution in accordance with Wilks' theorem. This theorem is upheld at the boundaries obtained from the likelihood ratio scan.

6.10.4 Unitarization

Operators with mass dimension greater than four can lead to interaction probabilities that increase with energy until unitarity is violated, causing the probability of interaction to exceed unity. To derive more physically meaningful limits, the EFT and interference terms are cut off beyond a specified energy threshold while retaining the Standard Model contributions at higher energies. Following the recommendations from the ATLAS aQGC task force, limits are reported for multiple cutoff scales as well as with no cutoff using a clipping scan. In this method, the fit is performed with EFT contributions removed beyond values of $M_{W\gamma} = 0.6$ TeV, 1.0 TeV, 1.5 TeV, 2.0 TeV, 3.0 TeV, and 4.0 TeV. The resulting limits are compared with the partial-wave unitarity constraints derived in [189].

The most stringent expected limits on each Wilson coefficient are derived from either the p_T^{jj} or p_T^l distributions. Observed and expected limits at the 95% CL on the Wilson coefficients are shown in Table 6.26 and Table 6.27, with or without the unitarity-preserving clipping technique introduced in Ref. [190].

The constraints on the dimension-8 Wilson coefficients are evaluated as a function of the cutoff scale, with the anomalous interaction contribution set to zero for $M_{W\gamma}$ values exceeding the cutoff. Figure 6.54 presents the clipping scan for the $T3$ operator when fitting the p_T^{jj} distribution. The p_T^{jj} observable is found to be most sensitive to tensor-type operators, while p_T^l is most sensitive to mixed scalar-type operators. The constraints placed on the f_{T3} and f_{T4} operators represent the first such limits obtained at the LHC.

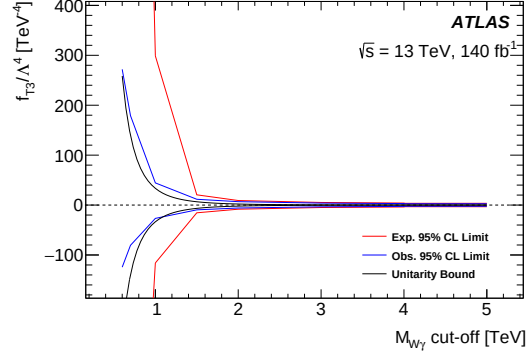


Fig. 6.54: Expected and observed 95% CL limits for the tensor-type operator coupling f_{T3} obtained from the fit to p_T^{jj} at various values of $m_{W\gamma}$. Bounds from partial wave unitarity constraints are also included.

6.11 Conclusion

Table. 6.26: Expected and observed limits on dimension-8 operators that modify the $WW\gamma\gamma$ coupling, based on fits to either the p_T^{jj} or p_T^l distribution.

Coefficients [TeV ⁻⁴]	Observable	Expected [TeV ⁻⁴]	Observed [TeV ⁻⁴]
f_{T0}/Λ^4	p_T^{jj}	[-2.4, 2.4]	[-1.8, 1.8]
f_{T1}/Λ^4	p_T^{jj}	[-1.5, 1.6]	[-1.1, 1.2]
f_{T2}/Λ^4	p_T^{jj}	[-4.4, 4.7]	[-3.1, 3.5]
f_{T3}/Λ^4	p_T^{jj}	[-3.3, 3.5]	[-2.4, 2.6]
f_{T4}/Λ^4	p_T^{jj}	[-3.0, 3.0]	[-2.2, 2.2]
f_{T5}/Λ^4	p_T^{jj}	[-1.7, 1.7]	[-1.2, 1.3]
f_{T6}/Λ^4	p_T^{jj}	[-1.5, 1.5]	[-1.0, 1.1]
f_{T7}/Λ^4	p_T^{jj}	[-3.8, 3.9]	[-2.7, 2.8]
f_{M0}/Λ^4	p_T^l	[-28, 28]	[-24, 24]
f_{M1}/Λ^4	p_T^l	[-43, 44]	[-37, 38]
f_{M2}/Λ^4	p_T^l	[-10, 10]	[-8.6, 8.5]
f_{M3}/Λ^4	p_T^l	[-16, 16]	[-13, 14]
f_{M4}/Λ^4	p_T^l	[-18, 18]	[-15, 15]
f_{M5}/Λ^4	p_T^l	[-17, 14]	[-14, 12]
f_{M7}/Λ^4	p_T^l	[-78, 77]	[-66, 65]

Table. 6.27: Expected and observed 95% CL limits for specified $M_{W\gamma}$ cutoff values, indicating where the expected limit intersects with the unitarity bounds derived from partial wave unitarity constraints. The limits are extracted from fits to either the p_T^{jj} or p_T^l distribution..

Coefficients [TeV ⁻⁴]	Observable	$M_{W\gamma}$ cut-off [TeV]	Expected [TeV ⁻⁴]	Observed [TeV ⁻⁴]
f_{T0}/Λ^4	p_T^{jj}	-	[-2.4, 2.4]	[-1.7, 1.8]
f_{T1}/Λ^4	p_T^{jj}	-	[-1.5, 1.6]	[-1.1, 1.2]
f_{T2}/Λ^4	p_T^{jj}	-	[-4.4, 4.7]	[-3.1, 3.5]
f_{T3}/Λ^4	p_T^{jj}	-	[-3.3, 3.5]	[-2.4, 2.6]
f_{T4}/Λ^4	p_T^{jj}	-	[-3.0, 3.0]	[-2.2, 2.2]
f_{T5}/Λ^4	p_T^{jj}	1.1	[-9.9, 9.9]	[-7.5, 7.5]
f_{T6}/Λ^4	p_T^{jj}	1.3	[-7.4, 7.6]	[-5.2, 5.4]
f_{T7}/Λ^4	p_T^{jj}	-	[-3.8, 3.9]	[-2.7, 2.8]
f_{M0}/Λ^4	p_T^l	-	[-38, 37]	[-38, 37]
f_{M1}/Λ^4	p_T^l	-	[-57, 58]	[-41, 42]
f_{M2}/Λ^4	p_T^l	0.8	[-110, 110]	[-88, 82]
f_{M3}/Λ^4	p_T^l	1.1	[-100, 110]	[-73, 77]
f_{M4}/Λ^4	p_T^l	1.0	[-118, 111]	[-89, 83]
f_{M5}/Λ^4	p_T^l	1.3	[-57, 80]	[-32, 77]
f_{M7}/Λ^4	p_T^l	-	[-96, 95]	[-69, 68]

The electroweak production of $W\gamma jj$ has been observed using ATLAS data corresponding to an integrated luminosity of 140 fb^{-1} at $\sqrt{s} = 13 \text{ TeV}$. This process offers a unique opportunity to probe quartic gauge couplings through vector boson scattering, particularly testing the $WW\gamma Z$ and $WW\gamma\gamma$ couplings predicted by the Standard Model. The measured fiducial cross-section for electroweak $W\gamma jj$ production is $13.2 \pm 2.5 \text{ fb}$, consistent with leading-order predictions from both MadGraph5+Pythia8 and Sherpa.

Advanced machine learning techniques, such as neural networks, are employed to enhance the sensitivity of the analysis. Neural network models are trained to separate signal from background events, improving the significance of the measurement. The differential cross-sections are measured using several kinematic observables, which are sensitive to quartic gauge couplings and potential CP-violating effects. These measurements are corrected for detector inefficiencies using iterative Bayesian unfolding methods and compared with theoretical predictions. While MadGraph5+Pythia8 tends to overestimate yields at high m_{jj} and p_T^{jj} , Sherpa shows better agreement, though it slightly underestimates the data across multiple observables. Both simulations, however, provide reasonable shape predictions.

The results are also interpreted in the framework of effective field theory, focusing on dimension-8 operators that modify quartic gauge couplings. The transverse momentum of the dijet system is proved to be most sensitive to tensor-type operators, while the lepton transverse momentum is the most responsive to mixed scalar operators. The first LHC constraints on the coefficients f_{T3} and f_{T4} are set, providing valuable input for future theoretical developments and searches beyond the Standard Model.

CHAPTER 7

Search for a resonance decaying into a scalar particle and a Higgs boson in the final state with two bottom quarks and two photons

7.1 Introduction

Despite the high precision of current experimental measurements of the Higgs boson's properties, such as its mass, couplings to other particles, and decay widths, there remains the possibility that H could exhibit minor mixing with additional scalar bosons, implying the presence of an extended Higgs sector. Numerous Beyond the Standard Model (BSM) theories forecast such an extended Higgs framework, wherein one of the physical Higgs boson states corresponds to the observed spin-0 boson with a mass of 125 GeV, while additional scalar particles are yet to be detected [191].

The decay process $X \rightarrow SH$ is allowed under the condition $m_X > m_S + m_H$. This phenomenon could emerge in models extending the SM Higgs sector with either a complex singlet [50] or two real singlets [89]. Models such as the complex two-Higgs-doublet model (2HDM) [88], the 2HDM with an extended real scalar singlet [90, 192], or the Next-to-Minimal Supersymmetric Standard Model (NMSSM) [91, 193] also allow for this decay process.

The Large Hadron Collider (LHC) has been instrumental in investigating the decay process $X \rightarrow SH$ under various benchmark scenarios [89, 194, 195]. The decay characteristics of the scalar particle S are dependent on both the model and the mass. The CMS Collaboration has conducted searches for the processes $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow b\bar{b})$, $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \tau\tau)$, and $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$ utilizing Run 2 data [196, 197, 198]. In the $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$ final state, CMS detected a deviation from the background-only hypothesis, reporting a local (global) significance of 3.8 (below 2.8) standard deviations for $m_X = 650$ GeV and

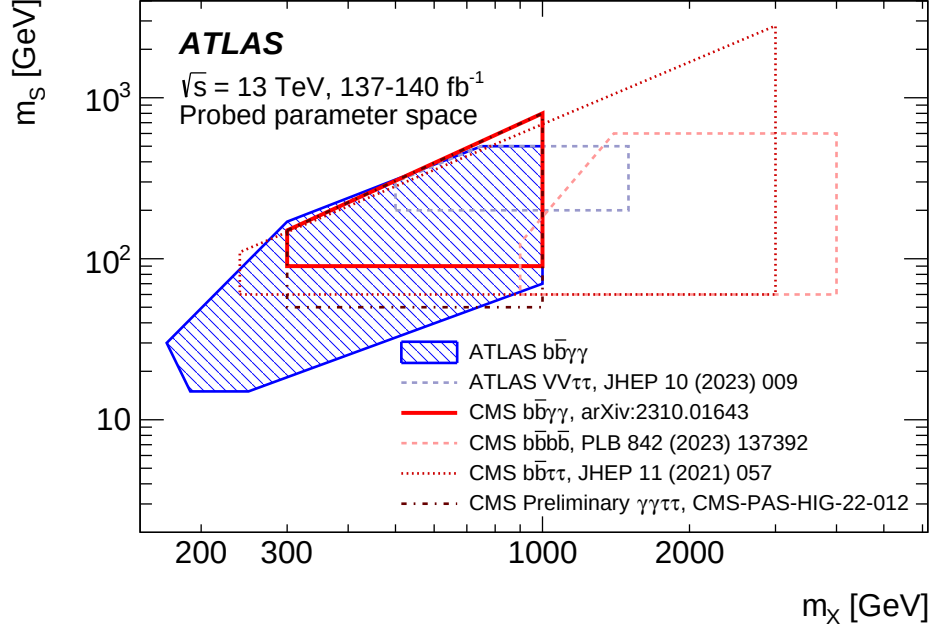


Fig. 7.1: The phase space explored in this $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$ analysis is compared with similar studies conducted by CMS and ATLAS, with details of the final states provided in the figure legend.

$m_S = 90$ GeV [199]. ATLAS has also released results concerning the search for $X \rightarrow S(\rightarrow VV)H(\rightarrow \tau\tau)$, where V represents a W or Z boson [200]. Figure 7.1 illustrates the phase spaces explored in these three CMS analyses, in comparison with those investigated by various ATLAS searches, including the current $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$ analysis.

This chapter concentrates on the search for $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$, utilizing the Run 2 dataset previously employed by ATLAS to investigate Higgs boson pair production [25]. The $H \rightarrow \gamma\gamma$ decay leads to a diphoton mass peak, while the $S \rightarrow b\bar{b}$ decay results in two b jets. Consequently, this produces a distinctive signal with three resonant mass peaks from $H \rightarrow \gamma\gamma$, $S \rightarrow b\bar{b}$, and $X \rightarrow b\bar{b}\gamma\gamma$. In scenarios where the scalar S has couplings analogous to the Standard Model (SM) Higgs boson, $S \rightarrow b\bar{b}$ is the dominant decay for $m_S < 130$ GeV. The Feynman diagram for the primary production mode of this process is depicted in Figure 7.2.

The production rate of the scalar X and the decay branching ratios $BR(X \rightarrow SH)$ and $BR(S \rightarrow b\bar{b})$ are highly model-dependent and contingent upon the parameters of the extended Higgs sector. Hence, the results are expressed as 95% confidence level (CL) upper limits on $\sigma(pp \rightarrow X) \times BR(X \rightarrow SH) \times BR(S \rightarrow b\bar{b}) \times BR(H \rightarrow \gamma\gamma)$, denoted as $\sigma(X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma)$, probing the m_X range between 170 and 1000 GeV and the m_S range between 15 and 500 GeV, rather than focusing on specific models.

The core analysis strategy employs a classification derived from a Parame-

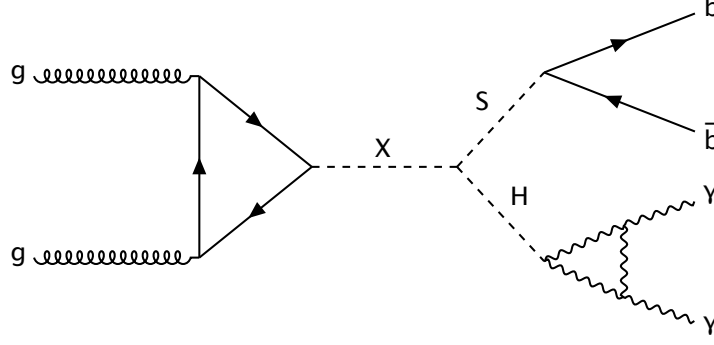


Fig. 7.2: An example of a Feynman diagram illustrating the gluon-gluon fusion production of a scalar particle X , which decays into a scalar S and a Standard Model Higgs boson. The scalar S subsequently decays into a pair of b -quarks, while the Higgs boson decays into two photons.

terised Neural Network (PNN). Initially, a selection process is applied, followed by the implementation of a PNN which incorporates the true signal masses m_X and m_S as parameters. The network is trained using all available signals and a subset of the background Monte Carlo (MC) data.

The diphoton mass range of 105–160 GeV is segmented into a control region (CR) for diphoton events with $m_{\gamma\gamma} \in [105, 120] \cup [130, 160]$ GeV, and a signal region (SR) with $m_{\gamma\gamma} \in [120, 130]$ GeV. In the CR, a single bin is utilized, whereas the SR is divided into multiple bins based on the PNN score distribution. This division allows the CR to control the normalization of the non-resonant diphoton background in both the SR and CR. The final likelihood is computed using the PNN score distribution for each signal point.

7.2 Samples

7.2.1 Data

The analysis utilizes pp collision data recorded by the ATLAS experiment at the LHC during Run 2, collected from 2015 to 2018. After applying detector and data quality cuts, the total integrated luminosity amounts to 140 fb^{-1} . This study employs the same trigger selection as the $HH \rightarrow b\bar{b}\gamma\gamma$ analysis [25]. Throughout Run 2, various sets of di-photon triggers were deployed.

In 2015 and 2016, a di-photon trigger with loose identification criteria, HLT_g35_loose_g25, was employed for events where the transverse energy (E_T) of the leading (sub-leading) photon exceeded 35 GeV (25 GeV). This trigger also required two distinct energy deposits exceeding 15 GeV at Level 1 [201]. From 2017 onwards, due to higher rates, a medium di-photon trigger,

HLT_g35_medium_g25_medium_L12EM20VH, was used, where L12EM20VH indicates the L1 di-electromagnetic (2EM) seed with a 20 GeV E_T threshold, varying with pseudorapidity, and additional hadronic core isolation (H).

Two single-photon triggers were also employed. In 2015, the HLT_g120_loose trigger, applying loose identification criteria and selecting photons with $E_T > 120$ GeV, was utilized. From 2016 to 2018, the HLT_g140_loose trigger, with a higher E_T threshold of 140 GeV, was adopted. A logical OR was applied between the single-photon and di-photon triggers.

The online trigger thresholds guide the offline di-photon selection. At the analysis level, the transverse momentum (p_T) of the leading (subleading) photon is required to be at least 35% (25%) of the invariant mass of the di-photon system. Additionally, a mass window selection of $m_{\gamma\gamma} \in [105, 160]$ GeV is imposed, corresponding to transverse energy thresholds of 36.75 GeV (26.25 GeV) for the leading (subleading) photon.

7.2.2 Signal MC

The BSM $X \rightarrow S(b\bar{b})H(\gamma\gamma)$ process, represented by the Feynman diagram in Figure 7.2, serves as the signal. Signal samples are generated for different (m_X, m_S) mass points. The mass ranges are selected to ensure $m_X - m_S > 125$ GeV (Higgs boson decay condition). For m_S set at 15 GeV, we obtain $m_X > 140$ GeV. The 1 TeV m_X limit arises from the required background fit statistics for the resonant H search with $m_X = 1200$ and 130 GeV, though the statistics were insufficient for the latter.

The Monte Carlo datasets utilized in this study are generated at leading order (LO) using Pythia 8 and EvtGen 1.7.0 to model the fragmentation of b -quarks. For the matrix element, the NNPDF 2.3 LO parton distribution function (PDF) set [202, 150] is applied, along with the A14 NNPDF23LO tune for simulating parton showers. Scalar particles X and S are produced under the Narrow-Width Approximation, a standard assumption covering all the models. The simulations are conducted using the Atlas Fast simulation framework (AF2 samples).

7.2.3 Background MC

Table 7.1 provides an overview of the samples employed as the nominal Standard Model background prediction. The analysis considers all single Higgs samples within the di-photon final state. Production modes encompass both common and rarer processes, with single-top associated production divided into two distinct samples: one for the s - and t -channel contributions (tHbj), and the other for the W -associated contributions (tHW).

The di-Higgs samples are analyzed in the $b\bar{b}\gamma\gamma$ final state, focusing on two primary production mechanisms: gluon-gluon fusion (ggHH) and vector-boson fusion (VBF). Notably, for the VBF case, contributions from the VHH process are excluded from the $pp \rightarrow HHjj$ generation. These samples are also used in the $HH \rightarrow b\bar{b}\gamma\gamma$ analysis [25] due to the investigation of identical final states.

Table. 7.1: Summary of the samples utilized as the nominal background prediction in this analysis.

DSID	Generator	PDF (ME)	PDF+Tune (PS)	Production Mode
Single Higgs				
343981	Powheg 2.3133 + Pythia 8	PDFLHC	AZNLOCTEQ6	ggH
346214	Powheg + Pythia 8	PDFLHC	AZNLOCTEQ6	VBF
345318	Powheg + Pythia 8.212	PDFLHC	AZNLOCTEQ6	$W + H$
345317	Powheg + Pythia 8.212	PDFLHC	AZNLOCTEQ6	$W - H$
345319	Powheg + Pythia 8.212	PDFLHC	AZNLOCTEQ6	$qq \rightarrow ZH$
345061	Powheg 2.3133 + Pythia 8.212	PDFLHC	AZNLOCTEQ6	$gg \rightarrow ZH$
346525	Powheg + Pythia 8.235	PDFLHC	A14NNPDF23	ttH
345315	Powheg 2.3133 + Pythia 8.212	PDFLHC	A14NNPDF23	$b\bar{b}H$
346188	MC@NLO + Pythia 8.230	NNPDF	A14NNPDF23	$tHbj$
346486	MC@NLO + Pythia 8.235	NNPDF	A14NNPDF23	tHW
di-Higgs				
600021	Powheg + Pythia 8.244.3	PDFLHC	A14NNPDF23	$ggHH$
503004	MadGraph 2.7.3p3.atlas6 + Pythia 8.244p3.rangefix	NNPDF	A14NNPDF23	VBF HH without VHH
QCD				
364352	Sherpa 2.2.4 (ME@NLO+PS)	NNPDF3.0 NNLO		Continuum background $\gamma\gamma + 0, 1(NLO), 2, 3(LO), m_{\gamma\gamma} \in 90 - 175$ GeV
345868	MadGraph5_AMC@NLO 2.3.3p1 + Pythia 8.212	NNPDF	A14NNPDF23	$tt\gamma\gamma$ (noallhad)
345869	MadGraph5_AMC@NLO 2.3.3p1 + Pythia 8.212	NNPDF	A14NNPDF23	$tt\gamma\gamma$ (allhad)
700508	Sherpa 2.2.11p3	NNPDF3.0 NNLO		$Z(\rightarrow q\bar{q})\gamma\gamma$ ($q = \text{light quark}$)
700509	Sherpa 2.2.11p3	NNPDF3.0 NNLO		$Z(\rightarrow b\bar{b})\gamma\gamma$

7.2.4 Alternative Monte Carlo for Systematics

Table 7.2 presents the samples employed to determine the theoretical systematic uncertainties affecting both the signal and the background predictions.

Table. 7.2: Summary of the samples employed to estimate theoretical systematic uncertainties on the signal and background predictions in this analysis.

DSID	Generator	PDF (ME)	PDF+Tune (PS)	Production Mode
Resonant Di-Higgs samples as a proxy for Parton Shower systematics on $X \rightarrow S(b\bar{b})H(\gamma\gamma)$ signal				
450529	MadGraph 2.6.1 + Herwig 7.7.1.3	NNPDF23LO	MMHT2014lo68cl	$pp \rightarrow X \rightarrow HH$ with $m_X = 280$ GeV
450517	MadGraph 2.6.1 + Pythia 8.235	NNPDF23LO	A14NNPDF23LO	$pp \rightarrow X \rightarrow HH$ with $m_X = 280$ GeV
450535	MadGraph 2.6.1 + Herwig 7.7.1.3	NNPDF23LO	MMHT2014lo68cl	$pp \rightarrow X \rightarrow HH$ with $m_X = 500$ GeV
450518	MadGraph 2.6.1 + Pythia 8.235	NNPDF23LO	A14NNPDF23LO	$pp \rightarrow X \rightarrow HH$ with $m_X = 500$ GeV
450541	MadGraph 2.6.1 + Herwig 7.7.1.3	NNPDF23LO	MMHT2014lo68cl	$pp \rightarrow X \rightarrow HH$ with $m_X = 1000$ GeV
450519	MadGraph 2.6.1 + Pythia 8.235	NNPDF23LO	A14NNPDF23LO	$pp \rightarrow X \rightarrow HH$ with $m_X = 1000$ GeV
Single Higgs for Parton Shower systematics				
346526	Powheg + Herwig 7	NNPDF30NLO	MMHT2014lo68cl	ttH
346879	Powheg + Herwig 7.1.3p1	NNPDF30NLO	MMHT2014lo68cl	$qq \rightarrow ZH$
di-Higgs for Parton Shower systematics				
600051	Powheg + Herwig 7.1.6p3	PDFLHC	MMHT2014lo68cl	$ggHH$
QCD for background modelling uncertainty				
508679	MC@NLO + Pythia 8.245p3.lhcb7	NNPDF30NLO	A14NNPDF23LO	Continuum background $\gamma\gamma + 2$ jets

7.3 Object definition and selection

The two final-state particles reconstructed for the analysis, photons and b -quark jets (b -jets), are described along with their respective selection criteria.

7.3.1 Photons

The photon selection criteria in this analysis adhere to the standard diphoton selection procedure commonly used in all $H \rightarrow \gamma\gamma$ analyses. The specific requirements are as follows:

- Two photons with tight identification and $|\eta| < 1.37$ or $1.52 < |\eta| < 2.37$ (excluding the LAr calorimeter crack region),
- $p_T/m_{\gamma\gamma} > 0.35$ for the leading photon and $p_T/m_{\gamma\gamma} > 0.25$ for the subleading photon,
- Isolation requirements: $\text{topoEtCone20} < 0.065 \times p_T$ and $\text{ptcone20} < 0.05 \times p_T$,
- Invariant mass of the photon pair ($m_{\gamma\gamma}$) within the range $[105, 160]$ GeV.

7.3.2 Jets

The reconstructed jet collection in this analysis utilizes the AntiKt4PFlowCustomVtxHggJets algorithm [201]. This Particle Flow (PFlow) algorithm generates lists of tracks and topo-clusters, including both unmodified and new topo-clusters formed through energy subtraction. The algorithm matches each track to a topo-cluster in the calorimeter, subtracting the expected deposited energy from each cell in the matched topo-clusters. If the remaining energy aligns with the expected shower fluctuations of a single particle’s signal, the topo-cluster remnants are removed [203].

All the jets in this analysis adhere to the following criteria:

- $p_T > 25$ GeV
- Anti- k_t with $R = 0.4$
- Rapidity $|y| < 4.4$
- Jet-Vertex Tagger (JVT) WP:Tight for jets with $p_T < 60$ GeV
- Jet cleaning WP:LooseBad

Additionally, central jets utilized for the $S \rightarrow b\bar{b}$ reconstruction are selected with $|\eta| < 2.5$.

7.3.3 b -jets

The determination of jet flavour is conducted using the DL1r deep-learning neural network [204]. The DL1r b -tagging algorithm relies on distinct characteristics of b -hadron decays, including the impact parameters of tracks and the reconstructed displaced vertices in the ID. Additionally, the DL1r network incorporates discriminating variables formed by the recurrent neural network (RNNIP) [205], which leverages spatial and kinematic correlations between tracks emanating from the same b -hadron. For each jet, DL1r computes three distinct probabilities p_b , p_c , and p_{light} for the jet to originate from a b , c , or light quark respectively. These

probabilities are integrated to determine the final discriminant. The DL1r algorithm is fine-tuned to enhance performance on particle-flow jets and extends its capabilities to very high p_T jets. Central jets with $|\eta| < 2.5$ are eligible for flavour tagging. The working points are defined based on a single criterion on the DL1r discriminant output distribution, which can be adjusted to achieve a specific b -jet efficiency for a comprehensive $t\bar{t}$ MC sample. In this analysis, the DL1r working point achieves a 77% efficiency for identifying jets containing b -hadrons in simulated $t\bar{t}$ events. At this working point, the misidentification rates are 1/130 for light-flavour jets and 1/4.9 for charm jets. Scale factors are utilized to rectify differences in b -tagging efficiency between data and simulation, measured as a function of the jet p_T using a likelihood-based method in a sample enriched in $t\bar{t}$ events [206].

Scale factors are applied to reconcile the discrepancies in b -tagging efficiency between data and simulation. For jets stemming from b quarks, the scale factors are evaluated as a function of jet p_T using a likelihood-based method in $t\bar{t}$ enriched samples [206]. Scale factors for jets originating from c quarks are determined in $t\bar{t}$ events containing a $W \rightarrow cs$ decay [207]. For jets of light flavour, the scale factors are derived using Z+jets events [208].

The energy of b -tagged jets is corrected to account for the potential contributions from muons due to semileptonic b -hadron decays. Further corrections are made for the undetected energy of neutrinos and out-of-cone effects, with scale factors computed as a function of the b -jet p_T from a $t\bar{t}$ MC sample. These corrections collectively enhance the resolution of the invariant mass of the two jets with the highest b -tagging discriminant by approximately 20%. This procedure closely follows the methodology outlined in Ref. [209].

7.3.4 Leptons

Electrons are reconstructed from energy deposits in the electromagnetic calorimeter that are matched to inner detector (ID) tracks [166]. They must satisfy $|\eta| < 2.47$, excluding the calorimeter transition region $1.37 < |\eta| < 1.52$, and have a transverse momentum $p_T > 10$ GeV. The selection requires electrons to meet a “medium” identification criterion, which incorporates variables such as shower shape, track-cluster matching, and Transition Radiation Tracker (TRT) parameters within a likelihood-based algorithm [166].

Muons are reconstructed from high-quality tracks found in the muon spectrometer (MS) [210]. These tracks are required to match ID tracks within $|\eta| < 2.5$. Muons must have $|\eta| < 2.7$ and $p_T > 10$ GeV and satisfy a “medium” identification criterion [165].

Both electrons and muons are associated with the primary vertex based on requirements for the tracks' longitudinal and transverse impact parameters, z_0 and d_0 , respectively. These conditions include $|z_0| \sin \theta < 0.5$ mm (where θ represents the track's polar angle) for both electrons and muons, and $|d_0|/\sigma_{d_0} < 5$ (3) for electrons (muons).

For this analysis, events are selected to have exactly zero electrons and muons.

7.3.5 Overlap removal

Overlap removal techniques are implemented to prevent the utilization of the same detector signals in the reconstruction of multiple objects. This analysis prioritizes photons by excluding jets, electrons, and muons located within $\Delta R < 0.4$ of a chosen photon. Subsequently, jets positioned within $\Delta R < 0.2$ of electrons are discarded. Lastly, electrons and muons within $\Delta R < 0.4$ of any remaining jet are eliminated.

7.4 Event selection

7.4.1 Selection

This analysis employs two sets of selection: 2 b -tagged and 1 b -tagged, as outlined in Table 7.3. The 2 b -tagged selection requires exactly two b -tagged jets at 77% WP, while the 1 b -tagged selection requires one. These categories are designed to explore different phase space regions: resolved b -jets and merged b -jets.

Given the stringent selection for both photons, the single-photon trigger contribution is minimal. After selection, at most 0.4% of events pass only the single-photon trigger.

Table. 7.3: Definitions of the selection criteria used in this analysis. Jets classified as central have $|\eta| < 2.5$.

	2 b -tagged	1 b -tagged
Number of tight and isolated photons	≥ 2	≥ 2
$m_{\gamma\gamma}$ [GeV]	$\in [105, 160]$	$\in [105, 160]$
Number of leptons	$= 0$	$= 0$
Number of central jets	$\in [2, 5]$	$\in [2, 5]$
Number of b -tagged jets @ 77% WP	$= 2$	$= 1$

The event yields for the MC signal are summarized in Table 7.4 for various (m_X, m_S) mass points, while the Run 2 data results are presented in Table 7.5.

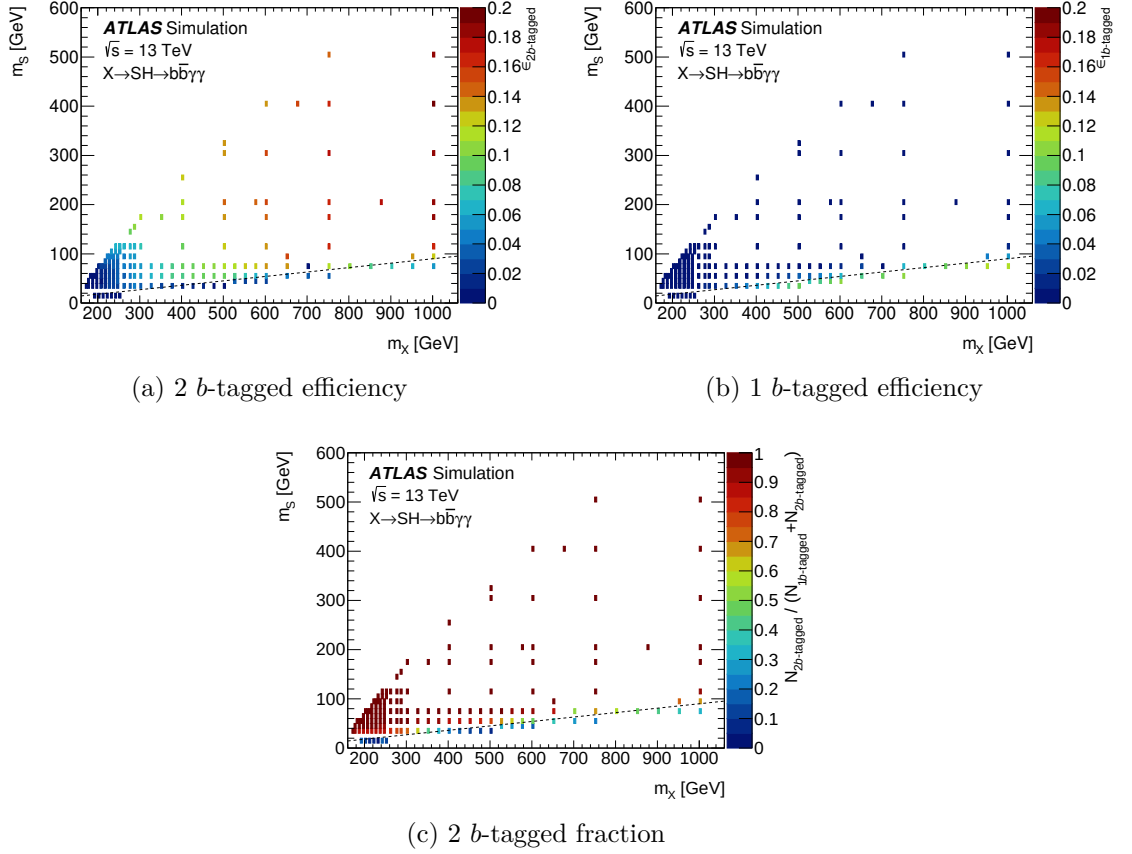


Fig. 7.3: The signal efficiency is displayed for (a) the 2 b -tagged selection, (b) the 1 b -tagged selection, and (c) the fraction of events classified in the 2 b -tagged category, as functions of the masses m_X and m_S . Signal yields are calculated within a $2\sigma_{CB}$ mass window around the peak values, obtained from fits to m_{bb} , m_b , $m_{b\gamma\gamma}^*$, and $m_{bb\gamma\gamma}^*$. The dashed line represents the separation between the two categories, which empirically corresponds to $m_S/m_X = 0.09$.

The predicted background yields for each selection are shown in Table 7.6. The 2 b -tagged selection generally selects more signal events than the 1 b -tagged selection in the analyzed mass space. The 1 b -tagged selection is more efficient in the large mass-splitting region where the two b hadrons merge into a single jet due to their boosted kinematics. This is illustrated in Figure 7.3, with the signal efficiency as a function of the m_X and m_S masses and the resulting fraction of events in the 2 b -tagged category. Therefore, the 2 b -tagged selection is applied in the resolved regions, and the 1 b -tagged one in the merged regions.

A challenging scenario arises when $m_X \gg m_S + m_H$. Here, the momentum of S is so high that the two b -jets in $S \rightarrow b\bar{b}$ are too close to each other to be reconstructed using standard ATLAS $R = 0.4$ jets. Figure 7.4a shows the TRUTH-level $\Delta R(b_1, b_2)$ distributions for signals of $m_S = 70$ GeV and various m_X values. The b quarks get closer with increasing m_X and $\Delta m(X, S)$. When $\Delta R(b_1, b_2)$ is small enough, the two will be reconstructed inside one $\Delta R = 0.4$ jet. The mass

Table. 7.4: Outflows for a subset of generated MC signal samples, assuming a signal cross-section of 1 fb.

Selection	(190,15) GeV		(250,110) GeV		(600,170) GeV		(1000,300) GeV	
	Yield	Efficiency	Yield	Efficiency	Yield	Efficiency	Yield	Efficiency
All events	148.18	100.0%	148.78	100.0%	144.19	100.0%	143.64	100.0%
Pass trigger	93.41	63.0%	97.40	65.5%	126.71	87.9%	133.82	93.2%
Has primary vertex	93.41	63.0%	97.40	65.5%	126.71	87.9%	133.82	93.2%
2 loose photons	73.44	49.6%	77.38	52.0%	86.76	60.2%	95.58	66.5%
$e - \gamma$ ambiguity	73.40	49.5%	77.35	52.0%	86.72	60.1%	95.55	66.5%
Trigger match	66.94	45.2%	70.35	47.3%	84.48	58.6%	94.85	66.0%
Photon tight ID cut	57.19	38.6%	59.72	40.1%	71.82	49.8%	80.21	55.8%
Photon isolation cut	49.60	33.5%	49.80	33.5%	65.62	45.5%	74.99	52.2%
Rel. p_T cuts	45.59	30.8%	46.01	30.9%	60.46	41.9%	71.61	49.9%
$m_{\gamma\gamma} \in [105, 160]$ GeV	45.56	30.7%	45.96	30.9%	60.37	41.9%	71.48	49.8%
$N_{\text{lepton}} = 0$	45.53	30.7%	45.9	30.9%	60.30	41.8%	71.34	49.7%
$N_{\text{central jets}} \in [2, 5]$	17.03	11.5%	30.42	20.4%	54.53	37.8%	68.62	47.8%
1 b -tagged selection	10.71	7.2%	14.67	9.9%	21.95	15.2%	24.31	16.9%
2 b -tagged selection	0.59	0.4%	9.94	6.7%	23.60	16.4%	30.83	21.5%

Table. 7.5: The number of events observed following the selection process in the Run 2 dataset.

Selection	2015	2016	2017	2018	Total Run 2	Efficiency
All events	30386848	225809920	217151872	270755072	744103712	100%
Pass trigger	25823596	208625392	185083712	239147808	658680508	88.5%
Has primary vertex	25820986	208619424	185054384	239139216	658063000	88.5%
2 loose photons	3614490	3649688	21857456	28374142	90342976	12.1%
$e - \gamma$ ambiguity	3614490	36410472	21857456	28374142	90265600	12.1%
Trigger match	2671857	27422110	13441074	14873584	62278825	8.4%
Photon tight ID cut	376969	3687760	4624282	6409823	15098839	2.0%
Photon isolation cut	151476	1464377	1852435	2485239	5954387	0.8%
Rel. p_T cuts	131391	1271544	1606093	2156352	5165380	0.7%
$m_{\gamma\gamma} \in [105, 160]$ GeV	28746	283207	370335	496814	1179102	0.2%
$N_{\text{lepton}} = 0$	28737	283009	370214	496694	1178654	0.16%
$N_{\text{central jets}} \in [2, 5]$	4020	40829	57632	75989	178470	0.02%
1 b -tagged selection	364	3861	5397	7308	16930	2.3×10^{-5}
2 b -tagged selection	34	435	595	810	1874	2.5×10^{-6}

Table. 7.6: Predicted background yields after applying the selection criteria.

Selection	1 b -tagged	2 b -tagged
HH ggF+VBF	1.827 ± 0.004	1.691 ± 0.004
Single Higgs	88.309 ± 0.22	20.069 ± 0.079
$Z(\rightarrow qq)\gamma\gamma$	53.729 ± 0.8	20.345 ± 0.303
$t\bar{t}\gamma\gamma$	49.818 ± 0.142	28.69 ± 0.109
$\gamma\gamma$ + jets	16309.7 ± 16.036	1418.32 ± 4.596
Total SM	16503.383 ± 16.058	1489.116 ± 4.608

points in the 1 b -tagged category are chosen empirically using the fractions shown in Figure 7.3. For these points, the expected limits in both categories will be

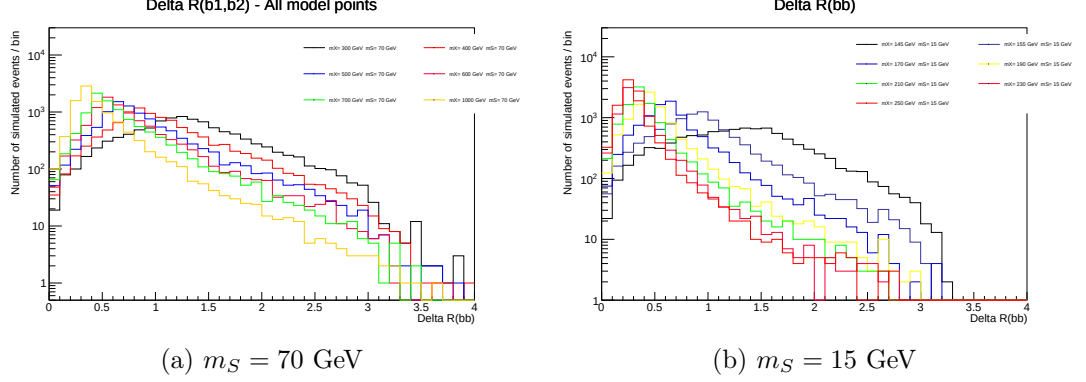


Fig. 7.4: The TRUTH-level $\Delta R_{b_1, b_2}$ distributions for signals with $m_S = 70$ GeV (a) and $m_S = 15$ GeV (b), each shown for multiple m_X values.

computed to ensure the most sensitive category is chosen. Figure 7.4b shows that for very low $m_S = 15$ GeV, signals with m_X as low as 190 GeV already encounter the b merging issue. The 1 b -tagged selection targets this challenging kinematic region, requiring only 1 b -jet at 77% b -tag WP. This assumes the merged b -jet can be tagged with the same efficiency as a standard b -jet.

Figures 7.5 illustrates the 2D plots of $m_b - m_{b\gamma\gamma}$ for the 1 b -tagged selection and $m_{bb} - m_{bb\gamma\gamma}$ for the 2 b -tagged selection. The 2D distributions of $m_b - m_{b\gamma\gamma}$ for the 1 b -tagged selection show mass peaks closer to m_S and m_X .

In the 1 b -tagged selection, the background composition differs from the 2 b -tagged selection, particularly for single Higgs MC samples. Figure 7.6 demonstrates the composition difference.

7.4.2 Parameterised Neural network discriminant

A Parametrised Neural Network (PNN) is highly suitable for this analysis, which aims to explore a vast phase space of signals characterized by the parameters m_X and m_S . The PNN is trained on a set of variables (x) to distinguish between signal and background, using the parameters (θ). Unlike a conventional Neural Network (NN) that is trained solely on x , a PNN learns the relationship between x and θ , effectively functioning as multiple NNs, each targeting specific θ values. This method optimizes computational efficiency by potentially substituting multiple neural networks with a single PNN, enabling interpolation across untrained signal regions. This approach is particularly advantageous for exploring a broad spectrum of signal hypotheses, especially in the regime where $m_X > 250$ GeV, thereby significantly improving the PNN's performance in signal reconstruction.

The PNN is constructed to distinguish signal from background over a wide range of (m_X, m_S) mass combinations, probing the Standard Model (SM) hypothesis. However, to evaluate a specific BSM scenario, one requires either a Monte

Carlo (MC) signal sample or an interpolated signal template. For clarity, the following discussion primarily focuses on the 2 b -tagged category.

The signal kinematics depend significantly on the masses m_X and m_S . Consequently, the reconstructed invariant masses of the final state particles, $m_{bb\gamma\gamma}$ and m_{bb} , serve as effective discriminants. A modified variable, $m_{bb\gamma\gamma}^*$, is defined as follows:

$$m_{bb\gamma\gamma}^* = m_{bb\gamma\gamma} - (m_{\gamma\gamma} - 125 \text{ GeV}). \quad (7.1)$$

This modification accounts for resolution effects in the $m_{\gamma\gamma}$ reconstruction, minimizing its correlation with the PNN score. It ensures that $m_{bb\gamma\gamma}^*$ remains uncorrelated with m_S , allowing the PNN to generalize effectively across different m_S mass points while preserving consistent input features.

The training dataset, detailed in Table 7.3, is utilized to train the PNN, with separate training conducted for the resolved and merged regions. The PNN is implemented using the Keras [211] and TensorFlow [212] frameworks. Optimal performance is achieved with input variables m_{bb} , $m^{bb\gamma\gamma}$, and $\theta = (m_X, m_S)$. The $m_{\gamma\gamma}$ distribution is excluded from the training inputs, but is instead used to define the Signal Regions (SR) and Control Regions (CR), aiding in background normalization and validating the PNN's output distribution by comparing data with Monte Carlo (MC) simulations. The correlation matrix in Figure 7.7 illustrates the reduced correlation between $m^{bb\gamma\gamma}$ and $m_{\gamma\gamma}$ compared to $m_{bb\gamma\gamma}$, highlighting the effectiveness of using $m_{bb\gamma\gamma}^*$ in the training process.

The dataset is divided into three folds, $Y \in \{1, 2, 3\}$, each containing an approximately equal number of events based on their event number. Fold Y encompasses events where $\text{EventNumber} \% 3 = Y - 1$. Three distinct PNNs are trained using cross-validation (CV) as delineated in Table 7.7. The training set is used for model training, the evaluation set (sometimes referred to as the test set) assesses the NN's performance, and the private test set is employed for statistical analysis once the final PNN is selected. The NN parameters were optimized using fold 1 of the CV. Various hyperparameter configurations, listed in Table 7.8, were tested with Keras Tuner [213]. This tool selected parameters that maximized the Area-Under-Curve (AUC) for the evaluation set, based on 40 rounds of Bayesian Optimization. Subsequent hyperparameter tuning considered the dataset's unique characteristics. Outlier removal from the m_{bb} and $m_{bb\gamma\gamma}^*$ distributions was conducted, specifically excluding the top and bottom 20% (for signal) and 5% (for background), along with an additional 5% from the combined distribution in the training dataset. Outliers were not excluded from the evaluation set or any CV folds used in the final training.

One of the primary challenges in training a NN to detect a specific $X \rightarrow SH$

Table. 7.7: Definitions of the training, evaluation, and private test sets for each PNN, trained using a cross-validation approach.

	CV 1	CV 2	CV 3
Training set	Fold 1	Fold 2	Fold 3
Evaluation set	Fold 2	Fold 3	Fold 1
Private test set	Fold 3	Fold 1	Fold 2

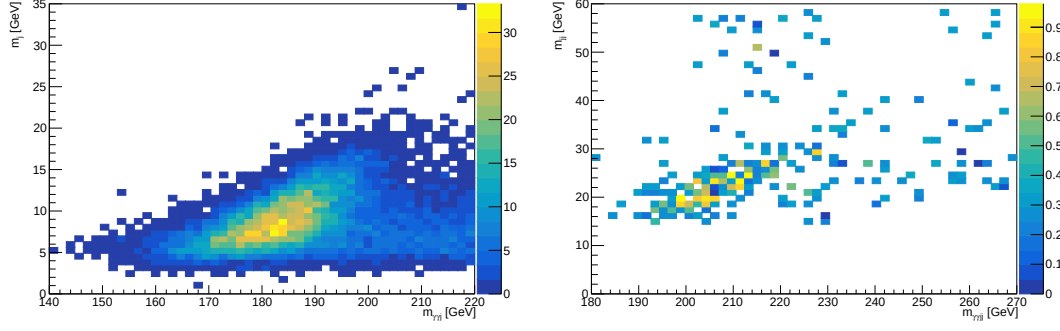
signal is the significant imbalance in event counts across different processes in the dataset. The proportion of signal events is substantially smaller than that of other processes. At the selection stage, most anticipated events are $\gamma\gamma + \text{jets}$ background, as demonstrated in Table 7.9. Consequently, NNs often classify all events as background, struggling to distinguish between different signals and backgrounds. The signal-to-background imbalance is mitigated by considering only the raw event counts without applying MC weights (including the signal cross-section), which led to the decision to exclude MC weights during training. The impact of MC weights on the kinematic distributions of input variables during training was negligible. The NNs were trained with class weights defined as $\text{weight}(i) = (1/\#i \text{ events}) \cdot (\# \text{ total events}/2.0)$ for $i = \text{signal or background}$. Additionally, an initial bias of $\log(\# \text{ signal events}/\# \text{ background events})$ was applied to the NN’s final layer. This configuration significantly improved the NN’s performance. Finally, the batch size was optimized to ensure that all signal processes had approximately 200 raw events per batch, minimizing high statistical fluctuations in the signal-to-background ratio between batches.

Table. 7.8: The PNN hyperparameters optimized using the Keras Tuner.

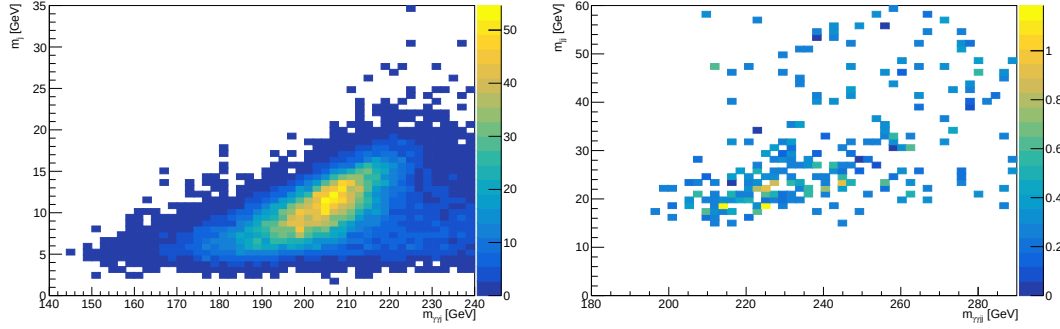
Parameter	Range	Sampling Mode
Number of hidden layers	[1–6]	1
Dropout rate (per-layer)	[0, 0.2]	0.05
Learning rate	[0.0001–0.1]	Log

Table. 7.9: The expected number of events for a luminosity of 140 fb^{-1} with a 2 b -tagged selection is shown for both the $m_{\gamma\gamma}$ side-band and the $m_{\gamma\gamma}$ peak (signal region, SR). A signal cross-section of 1 fb is assumed, and the yields listed are pre-fit estimates.

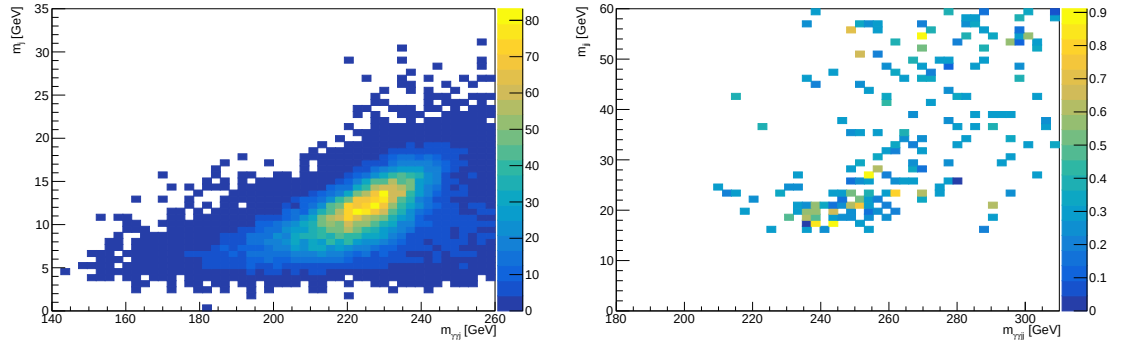
	Selection	Side-band	SR
HH ggF+VBF	1.691 ± 0.004	0.027 ± 0.001	1.664 ± 0.004
ZH	3.691 ± 0.013	0.073 ± 0.002	3.617 ± 0.013
WH	0.207 ± 0.004	0.005 ± 0.001	0.203 ± 0.004
$VBFH$	0.685 ± 0.012	0.014 ± 0.002	0.671 ± 0.012
bbH	0.62 ± 0.023	0.017 ± 0.004	0.603 ± 0.023
ggH	5.453 ± 0.065	0.109 ± 0.009	5.345 ± 0.065
$tHjb$	0.969 ± 0.029	0.022 ± 0.004	0.947 ± 0.029
tWH	0.131 ± 0.005	0.003 ± 0.001	0.128 ± 0.005
ttH	8.313 ± 0.014	0.206 ± 0.002	8.107 ± 0.014
$Z(\rightarrow qq)\gamma\gamma$	20.345 ± 0.303	16.362 ± 0.271	3.983 ± 0.136
$t\bar{t}\gamma\gamma$	28.69 ± 0.109	22.939 ± 0.097	5.751 ± 0.049
$\gamma\gamma$ +jets	1418.32 ± 4.596	1134.23 ± 4.11	284.088 ± 2.056
Total SM	1489.116 ± 4.608	1174.006 ± 4.12	315.108 ± 2.063
Data	-	1479	-
NF $_{\gamma\gamma$ +jets	-	1.26 ± 0.03	-
$m_{X,S} = (190, 50)$	1.236 ± 0.043	0.06 ± 0.009	1.176 ± 0.042
$m_{X,S} = (250, 110)$	9.942 ± 0.121	0.468 ± 0.026	9.474 ± 0.118
$m_{X,S} = (300, 110)$	11.311 ± 0.13	0.501 ± 0.027	10.81 ± 0.127
$m_{X,S} = (600, 170)$	23.634 ± 0.188	0.742 ± 0.033	22.892 ± 0.185
$m_{X,S} = (750, 300)$	28.151 ± 0.206	0.844 ± 0.036	27.306 ± 0.203
$m_{X,S} = (1000, 300)$	30.881 ± 0.215	0.864 ± 0.036	30.018 ± 0.212



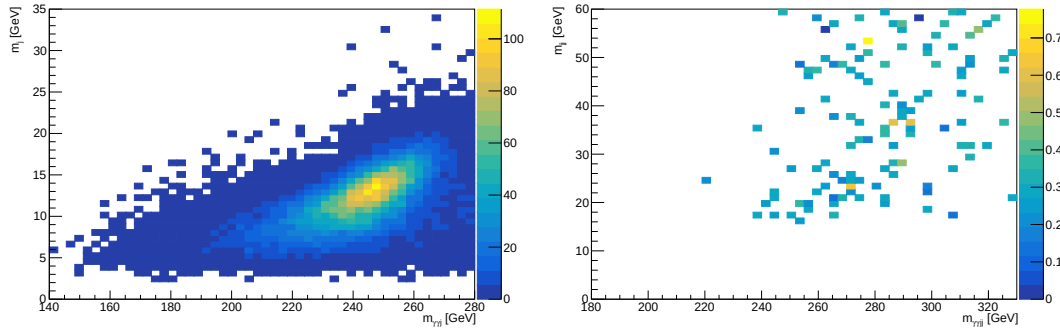
(a) $m_X = 190$ GeV, $m_S = 15$ GeV



(b) $m_X = 210$ GeV, $m_S = 15$ GeV



(c) $m_X = 230$ GeV, $m_S = 15$ GeV



(d) $m_X = 250$ GeV, $m_S = 15$ GeV

Fig. 7.5: 2D plots of $m_b - m_{b\gamma\gamma}$ for the 1 b -tagged selection (left) and $m_{bb} - m_{bb\gamma\gamma}$ for the 2 b -tagged selection (right) are shown for $m_S = 15$ GeV and signal MC samples with (a) $m_X = 190$ GeV, (b) $m_X = 210$ GeV, (c) $m_X = 230$ GeV, and (d) $m_X = 250$ GeV. The normalization is arbitrary but is kept consistent across both selections.

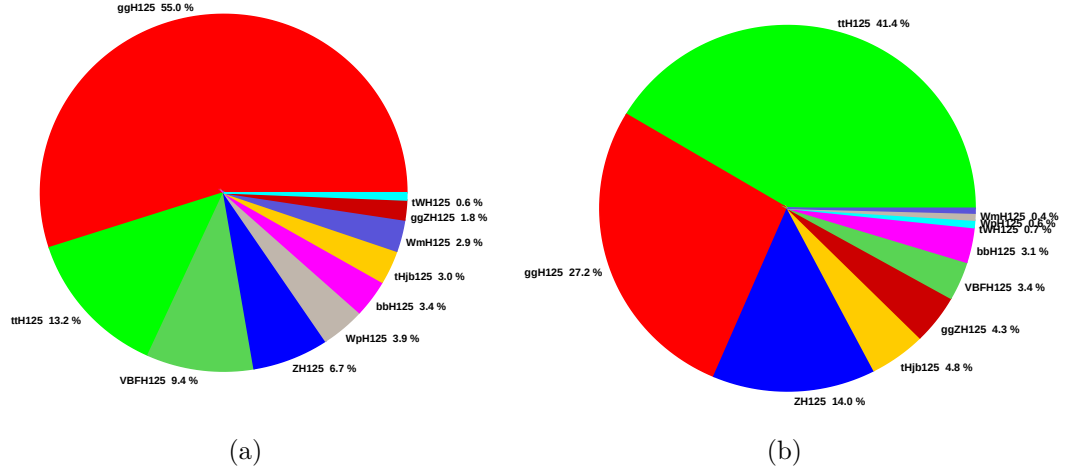


Fig. 7.6: The background composition of single Higgs MC samples is shown. The top figure (a) corresponds to the 1 b -tagged selection, while the bottom figure (b) corresponds to the 2 b -tagged selection.

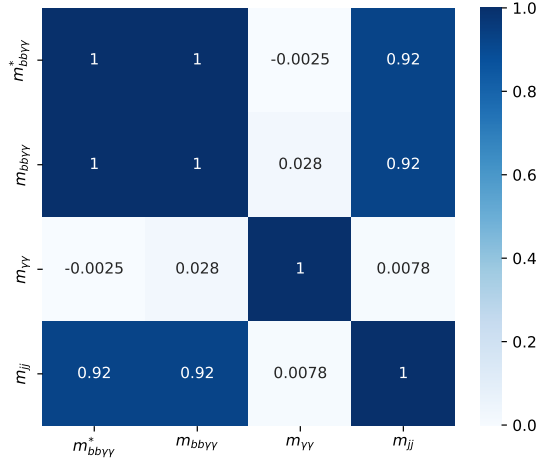


Fig. 7.7: The correlation matrix of the invariant masses for a signal sample with $(m_X, m_S) = (230, 90)$ GeV is presented.

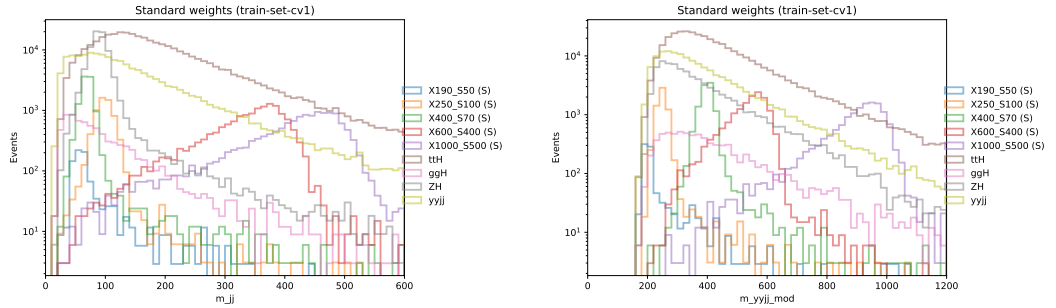


Fig. 7.8: The input training variables for the resolved PNN are presented, with only a subset of the signals displayed.

7.4.2.1 Resolved Region

In the resolved region, a dedicated Parameterised Neural Network (PNN) is trained to differentiate all Monte Carlo (MC) signals with $m_S/m_X \lesssim 0.09$ from the background. The 2 b -tagged selection is mandatory, utilizing m_{bb} and $m_{bb\gamma\gamma}^*$ as input variables.

This network is trained using the continuum ($\gamma\gamma$ +jets), $t\bar{t}H$, ggH , and ZH as backgrounds. The architecture and hyperparameters of the final PNN structure are depicted in Figure 7.9, while the remaining hyperparameters are listed in Table 7.10. Each cross-validation (CV) fold is trained for 2000 epochs, resulting in an Area Under the Curve (AUC) of 0.97 for both the training and evaluation test sets for CV fold 2, as shown in Figure 7.9, and 0.98 for CV folds 1 and 3.

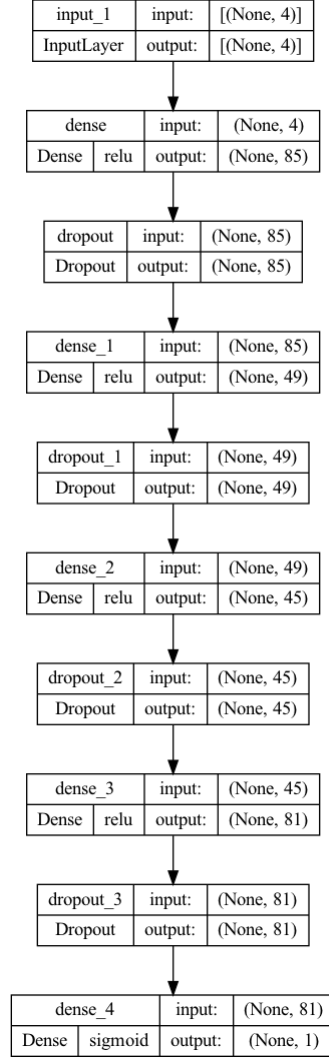


Fig. 7.9: The architecture of the PNN used in the resolved region is described. The input layer contains 4 nodes, representing 2 training variables and 2 parameters, while the output layer includes a single node with a sigmoid activation function, typical for binary classification. The network is composed of 4 hidden layers, each consisting of a standard dense layer with a rectified linear unit (ReLU) activation function, followed by a dropout layer. The number of nodes in each hidden layer, optimized through hyperparameter tuning, is specified. The dropout rate for each hidden layer is detailed in Table 7.10.

Table. 7.10: The hyperparameters of the PNN implemented in the resolved region.

Number of hidden layers	4
Layer 1 dropout rate	0.05
Layer 2 dropout rate	0.1
Layer 3 dropout rate	0.2
Layer 4 dropout rate	0.1
Learning rate	0.009137
Optimizer	Adam
Loss function	Binary Loss
Initial bias	0.118
Signal class weight	0.945
Background class weight	1.062
Batch size	212613
Number of batches	2
Number of epochs	2000

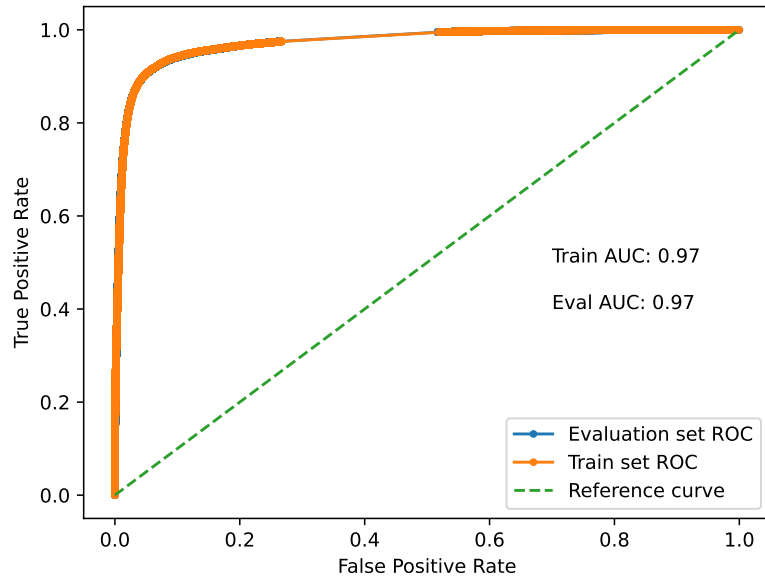


Fig. 7.10: The ROC curve for the PNN applied in the Resolved region, corresponding to CV 2. The AUC for both the training and evaluation sets reaches 0.98 in CV 1, which was used for hyperparameter optimization, as well as in CV 3.

7.4.2.2 Merged Region

A Parameterised Neural Network (PNN) is also implemented in the merged region to distinguish signals with varying (m_X, m_S) from the backgrounds within the 1 b -tagged selection, as outlined in Table 7.3. This PNN is trained independently from the one used in the resolved region. The training employs $t\bar{t}H$, ZH , ggH , $VBFH$, HH , and $\gamma\gamma + \text{jets}$ MC events as backgrounds. Signals with $m_S = 15$ GeV, which are only identifiable by the 1 b -tagged region, and signals with $(m_X, m_S) = (400, 30), (500, 30), (750, 70), \text{ and } (1000, 70)$ GeV are also incorporated into the training. Although these signals might be targeted by the 1 or 2 b -tagged regions, superior performance is anticipated for the 1 b -tagged selection, as illustrated in Figure 7.3. The final division between the two regions is based on the expected limits.

Initially, the training variables were set to be $\mathbf{x} = (m_b, m_{b\gamma\gamma}^*)$ with network parameters $\boldsymbol{\theta} = (m_X, m_S)$. Since m_b is not well calibrated, $p_T^{b\text{-jet}}$ is used instead of m_S . Figure 7.11 presents the 2D plots of $p_T^b - m_b$ and $p_T^b - m_{b\gamma\gamma}$ for the 1 b -tagged selection. The current merged region PNN is trained with $\mathbf{x} = (p_T^{b\text{-jet}}, m_{b\gamma\gamma}^*)$ and $\boldsymbol{\theta} = m_X$ to avoid issues with the uncalibrated m_b . The merged region targets signals with a broad range of m_X values and low m_S . Thus, parameterizing the NN as a function of a single parameter m_X is suitable for this region. The input variable distributions are presented in Figure 7.12 for the 1 b -tagged selection.

The architecture and hyperparameters of the initial PNN structure are shown in Figure 7.13, and the remaining hyperparameters are listed in Table 7.11. The ROC curve for CV fold 1, for both training and evaluation test sets, is displayed in Figure 7.14. For CV1, CV2, and CV3 folds, the AUC values are consistently 0.94.

Table. 7.11: The hyperparameters utilized for the PNN in the merged region are provided.

Number of hidden layers	3
Layer 1 dropout rate	0.02
Layer 2 dropout rate	0.2
Layer 3 dropout rate	0.2
Learning rate	0.0001798
Optimizer	Adam
Loss function	Binary Loss
Initial bias	-2.207
Signal class weight	5.044
Background class weight	0.555
Batch size	15299
Number of batches	63
Number of epochs	1000

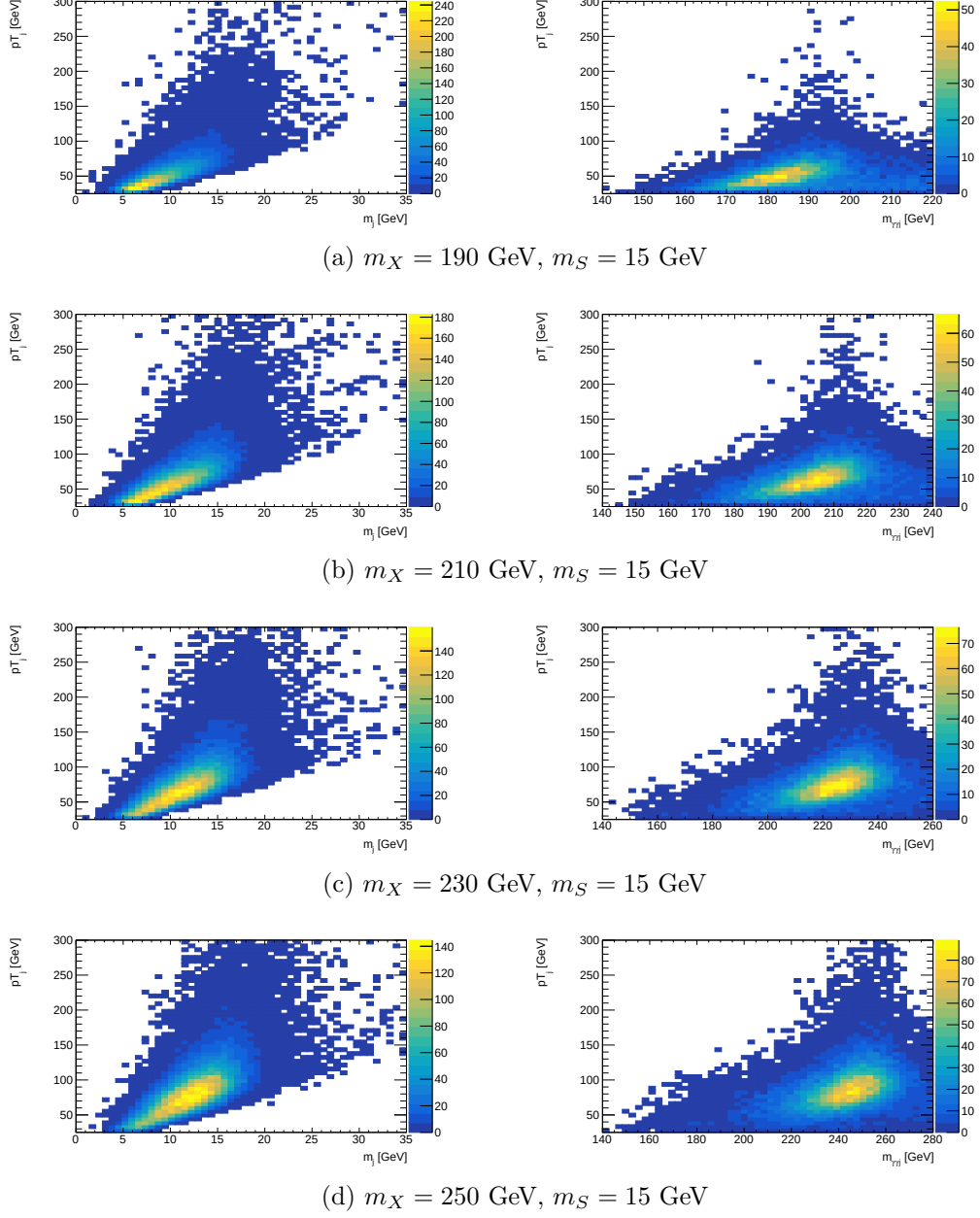


Fig. 7.11: 2D plots of $p^bT - mb$ and $p^bT - mb\gamma\gamma$ are shown for the 1 b -tagged selection with $m_S = 15$ GeV. The signal MC samples correspond to (a) $m_X = 190$ GeV, (b) $m_X = 210$ GeV, (c) $m_X = 230$ GeV, and (d) $m_X = 250$ GeV. The normalization is arbitrary but kept consistent across both selections.

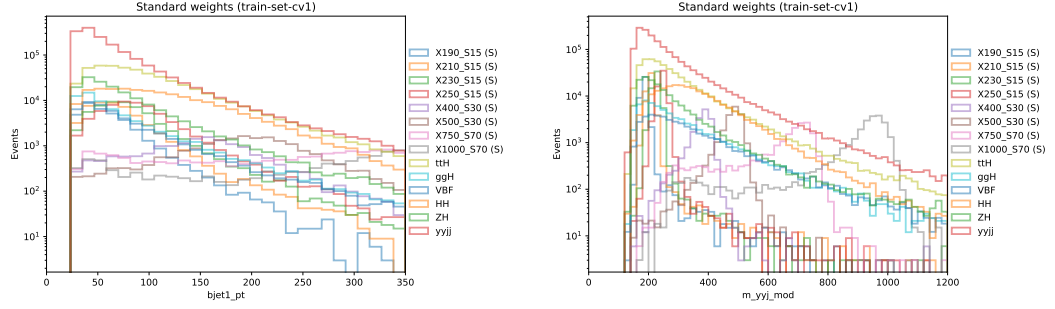


Fig. 7.12: The input training variables for the Merged PNN are presented, with one subset of signals (CV1) displayed.

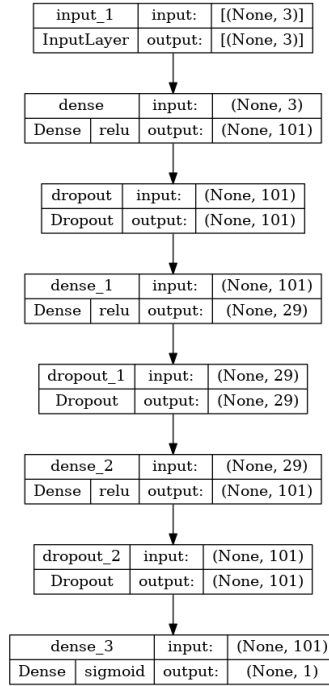


Fig. 7.13: The architecture of the PNN applied in the merged region is described. The input layer contains 3 nodes, representing 2 training variables and 1 parameter, while the output layer consists of a single node with a sigmoid activation function, commonly used for binary classification. The network includes 3 hidden layers. The specific dropout rate for each hidden layer is detailed in Table 7.11.

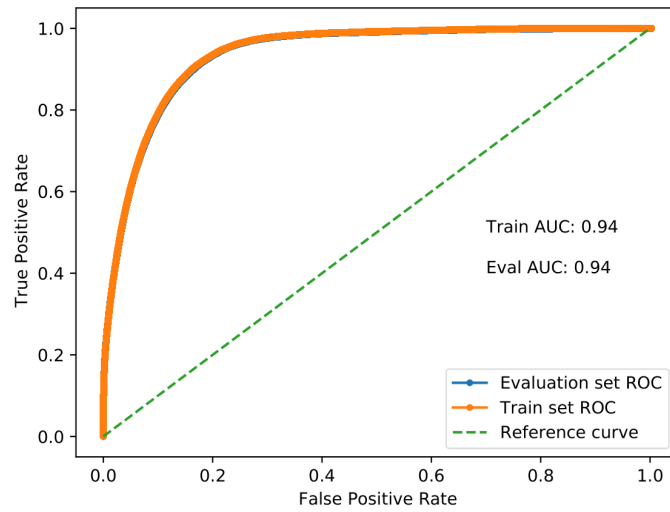


Fig. 7.14: The ROC curve for the PNN applied in the merged region is shown, corresponding to CV 1.

7.4.3 Signal Regions

All signal processes exhibit the same $H \rightarrow \gamma\gamma$ decay, resulting in a $m_{\gamma\gamma}$ distribution peaking at 125 GeV. Thus, $m_{\gamma\gamma}$ is utilized to further classify events into the Signal Region (SR) and Control Region (CR, also known as the side-band). Events with $120 \text{ GeV} < m_{\gamma\gamma} < 130 \text{ GeV}$ are selected by the SR, while those not meeting this criterion are included in the side-band and used to correct the normalization of the continuum background predicted by MC.

Table. 7.12: The signal-to-background ratio at the selection stage, in the $m_{\gamma\gamma}$ side-band, and at the $m_{\gamma\gamma}$ peak (signal region, SR) is presented. A signal cross-section of 1 fb is assumed for the calculations.

	Selection	Side-band	SR
$m_{X,S} = (190, 50)$	0.00084	$5e - 05$	0.00378
$m_{X,S} = (250, 110)$	0.00677	0.0004	0.03047
$m_{X,S} = (300, 110)$	0.00771	0.00043	0.03476
$m_{X,S} = (600, 170)$	0.0161	0.00064	0.07362
$m_{X,S} = (750, 300)$	0.01918	0.00073	0.08781
$m_{X,S} = (1000, 300)$	0.02104	0.00075	0.09653

7.4.3.1 Resolved Region

Signals with $m_S/m_X \lesssim 0.09$ fall into the Resolved Region, which employs a 2 b -tagged selection. Table 7.9 shows the expected number of events in various subsets of the Resolved Region. Table 7.12 details the signal-to-background ratio for signals with cross-sections of 1 fb. Figure 7.15 illustrates the PNN discriminant for specific m_X and m_S pairs in the SR ($m_{\gamma\gamma}$ peak). The ratio panel presents the signal-to-background ratio for each bin. The SR is binned according to the PNN score distribution using the TransfoJ algorithm from TRexFitter, ensuring at least one background event in the most signal-like bin N ($\text{PNN}(m_X, m_S) \sim 1$). Bins are added iteratively so that bin $N-i$ contains at least $i+1$ events for $i = 0, 1, \dots, k-1$. This procedure stops at bin $N-k$ if the signal-to-background ratio in the new bin is less than that of the full un-binned distribution. A single background-like bin is used for the remaining distribution ($\text{PNN}(m_X, m_S) \sim 0$). A single bin CR is used to obtain the normalization factor for the $\gamma\gamma$ +jets background $\mu_{\gamma\gamma}$ from data events in the side-band.

7.4.3.2 Merged Region

In the Merged Region, a 1 b -tagged selection is utilized. Table 7.13 lists the expected number of events in various subsets of the Merged Region. Table 7.14

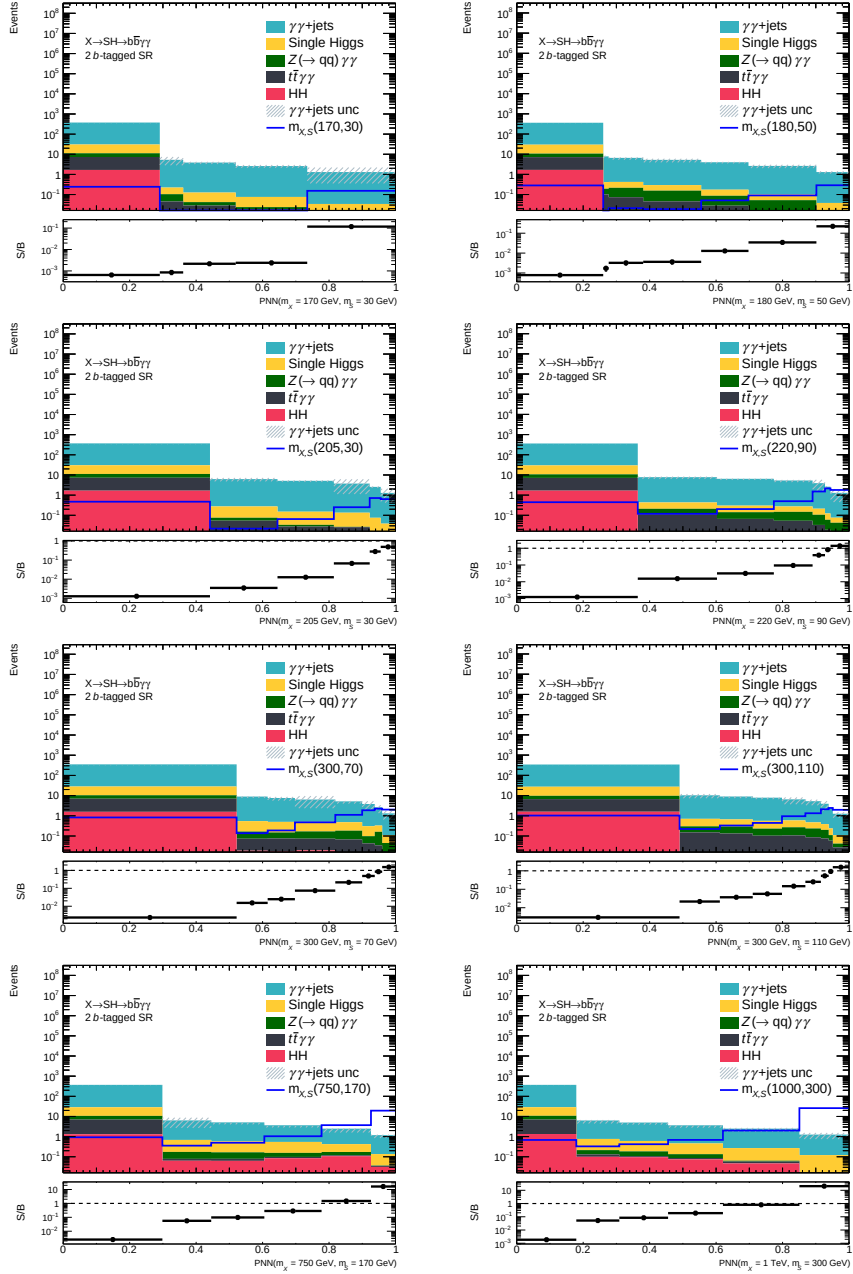


Fig. 7.15: Signal-to-background comparisons of the PNN score (m_X, m_S) in the $m_{\gamma\gamma}$ signal region (SR). The $\gamma\gamma$ +jets MC is normalized to the data in the side-band. The uncertainty band for $\gamma\gamma$ +jets includes the quadrature sum of the statistical uncertainty from the MC and the modelling systematic uncertainty. A signal cross-section of 1 fb is assumed for these comparisons.

provides the signal-to-background ratio for signals with cross-sections of 1 fb. Figure 7.16 displays the PNN score distributions for specific signal (m_X, m_S) and backgrounds in the SR ($m_{\gamma\gamma}$ peak). Binning is optimized using the TransfoJ algorithm, with additional manual bin merging to reduce bin numbers and avoid fluctuations in uncertainty studies.

Table. 7.13: The expected number of events for a luminosity of 140 fb^{-1} with a 1 b -tagged selection in the Merged region, covering both the $m_{\gamma\gamma}$ side-band and the $m_{\gamma\gamma}$ peak (signal region, SR). A signal cross-section of 1 fb is assumed. The yields provided are pre-fit estimates.

	Selection	Side-band	SR
HH ggF+VBF	1.827 ± 0.004	0.031 ± 0.001	1.796 ± 0.004
ZH	7.525 ± 0.018	0.169 ± 0.003	7.356 ± 0.018
WH	5.972 ± 0.021	0.145 ± 0.003	5.827 ± 0.021
$VBFH$	8.337 ± 0.042	0.182 ± 0.006	8.155 ± 0.041
bbH	2.976 ± 0.047	0.101 ± 0.008	2.875 ± 0.046
ggH	48.557 ± 0.202	1.206 ± 0.032	47.351 ± 0.199
$tHjb$	2.683 ± 0.05	0.054 ± 0.008	2.629 ± 0.05
tWH	0.572 ± 0.01	0.013 ± 0.001	0.559 ± 0.009
ttH	11.687 ± 0.017	0.31 ± 0.003	11.377 ± 0.017
$Z(\rightarrow qq)\gamma\gamma$	53.729 ± 0.8	42.694 ± 0.716	11.035 ± 0.357
$t\bar{t}\gamma\gamma$	49.818 ± 0.142	39.778 ± 0.127	10.04 ± 0.064
$\gamma\gamma$ +jets	16309.7 ± 16.036	13030.1 ± 14.334	3279.61 ± 7.189
Total SM	16503.383 ± 16.058	13114.781 ± 14.352	3388.612 ± 7.202
Data		13450	
NF $_{\gamma\gamma+\text{jets}}$	-	1.03 ± 0.01	-
$m_{X,S} = (190, 15)$	10.715 ± 0.057	0.48 ± 0.012	10.235 ± 0.055
$m_{X,S} = (210, 15)$	13.952 ± 0.065	0.645 ± 0.014	13.307 ± 0.063
$m_{X,S} = (230, 15)$	16.084 ± 0.07	0.702 ± 0.014	15.382 ± 0.068
$m_{X,S} = (250, 15)$	17.811 ± 0.074	0.773 ± 0.015	17.038 ± 0.072
$m_{X,S} = (400, 30)$	22.951 ± 0.187	0.83 ± 0.036	22.121 ± 0.184
$m_{X,S} = (500, 30)$	27.627 ± 0.205	0.917 ± 0.037	26.709 ± 0.202
$m_{X,S} = (600, 40)$	29.426 ± 0.092	0.905 ± 0.016	28.52 ± 0.09
$m_{X,S} = (750, 50)$	32.243 ± 0.096	0.928 ± 0.016	31.315 ± 0.094
$m_{X,S} = (750, 70)$	27.214 ± 0.204	0.807 ± 0.035	26.406 ± 0.201
$m_{X,S} = (1000, 70)$	34.298 ± 0.227	0.965 ± 0.038	33.333 ± 0.224

7.4.4 Data/MC Comparison

7.4.4.1 Resolved Region

Figure 7.17 displays the data-to-simulation comparison in the side-band for $m_{\gamma\gamma}$, m_{bb} , $m_{bb\gamma\gamma}$, and $m_{bb\gamma\gamma}^*$. Figure 7.18 shows the comparison for PNN scores (m_X, m_S). A normalization factor of 1.26 ± 0.03 , derived from fitting the side-band data, is applied to the $\gamma\gamma$ +jets MC prediction. Only the Sherpa $\gamma\gamma$ +jets MC prediction is required to model the QCD continuum background. There is no need to include γ -jets or dijet data-driven templates. The shapes of all distributions are accurately predicted by the simulation within uncertainties.

Table. 7.14: Signal-to-background ratio at 1 b -tagged selection, $m_{\gamma\gamma}$ side-band and $m_{\gamma\gamma}$ peak (SR) for signals of Merged region. Signal cross-sections of 1 fb are used.

	Selection	Side-band	SR
$m_{X,S} = (190, 15)$	0.00065	$4e - 05$	0.00302
$m_{X,S} = (210, 15)$	0.00085	$5e - 05$	0.00393
$m_{X,S} = (230, 15)$	0.00097	$5e - 05$	0.00454
$m_{X,S} = (250, 15)$	0.00108	$6e - 05$	0.00503
$m_{X,S} = (400, 30)$	0.00139	$6e - 05$	0.00653
$m_{X,S} = (500, 30)$	0.00167	$7e - 05$	0.00788
$m_{X,S} = (600, 40)$	0.00178	$7e - 05$	0.00842
$m_{X,S} = (750, 50)$	0.00195	$7e - 05$	0.00924
$m_{X,S} = (750, 70)$	0.00165	$6e - 05$	0.00779
$m_{X,S} = (1000, 70)$	0.00208	$7e - 05$	0.00984

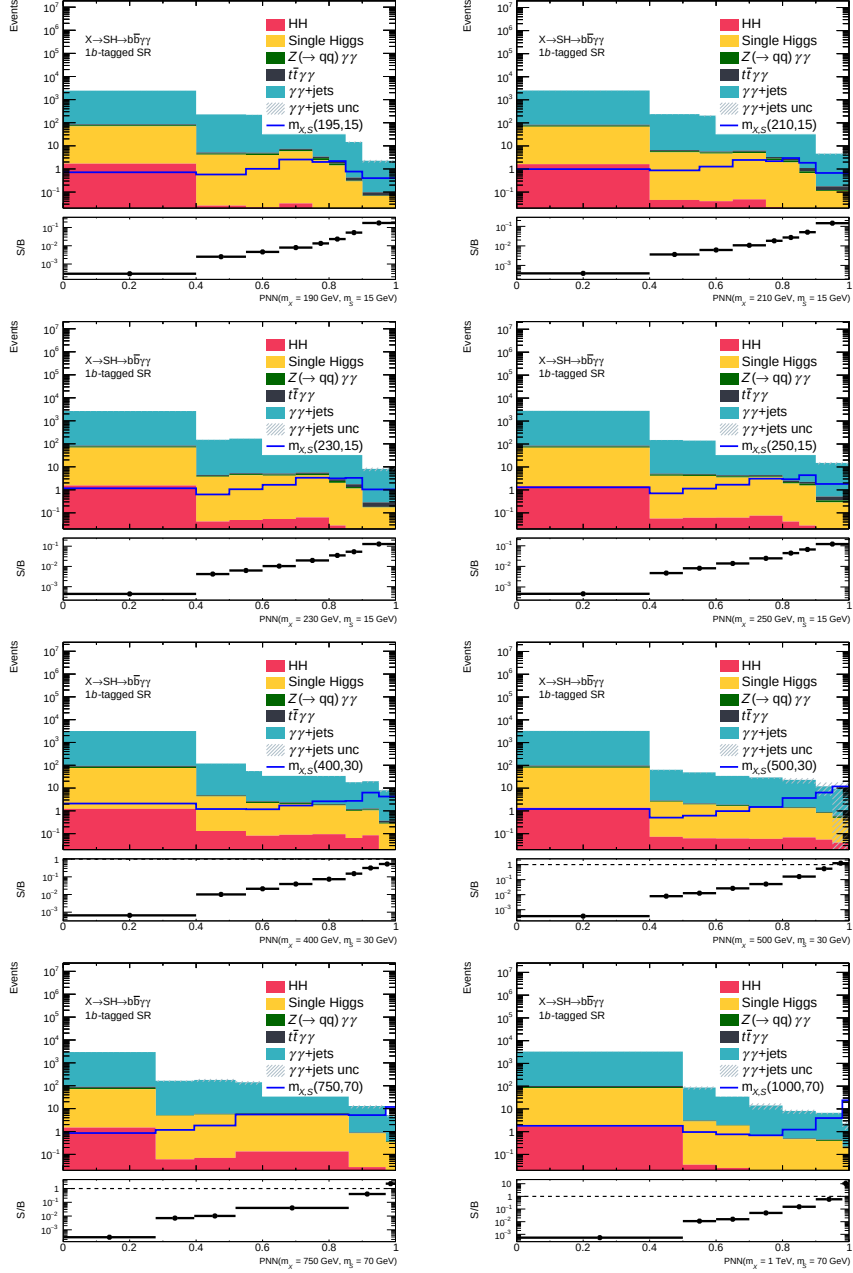


Fig. 7.16: Signal-to-background comparisons of the PNN score (m_X, m_S) in the Merged region within the $m_{\gamma\gamma}$ signal region (SR). The $\gamma\gamma$ +jets MC is normalized to data in the side-band. The uncertainty band for $\gamma\gamma$ +jets combines the statistical uncertainty from the MC and the modelling systematic uncertainty, summed in quadrature. Signal cross-sections of 1 fb are assumed for the analysis.

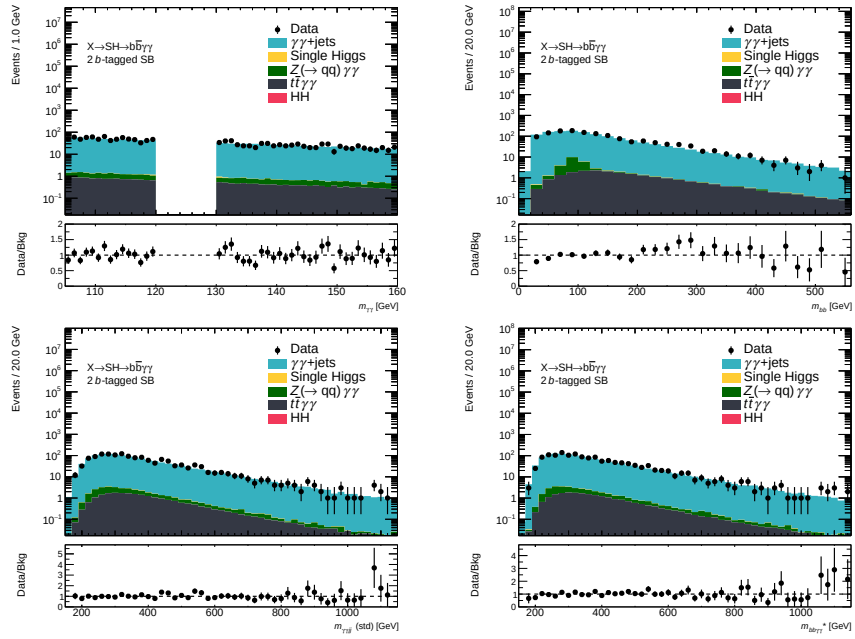


Fig. 7.17: Post-fit comparisons between data and simulation for the $m_{\gamma\gamma}$, m_{bb} , $m_{bb\gamma\gamma}$, and $m_{bb\gamma\gamma}^*$ distributions in the side-band region, following the 2 b -tagged selection.

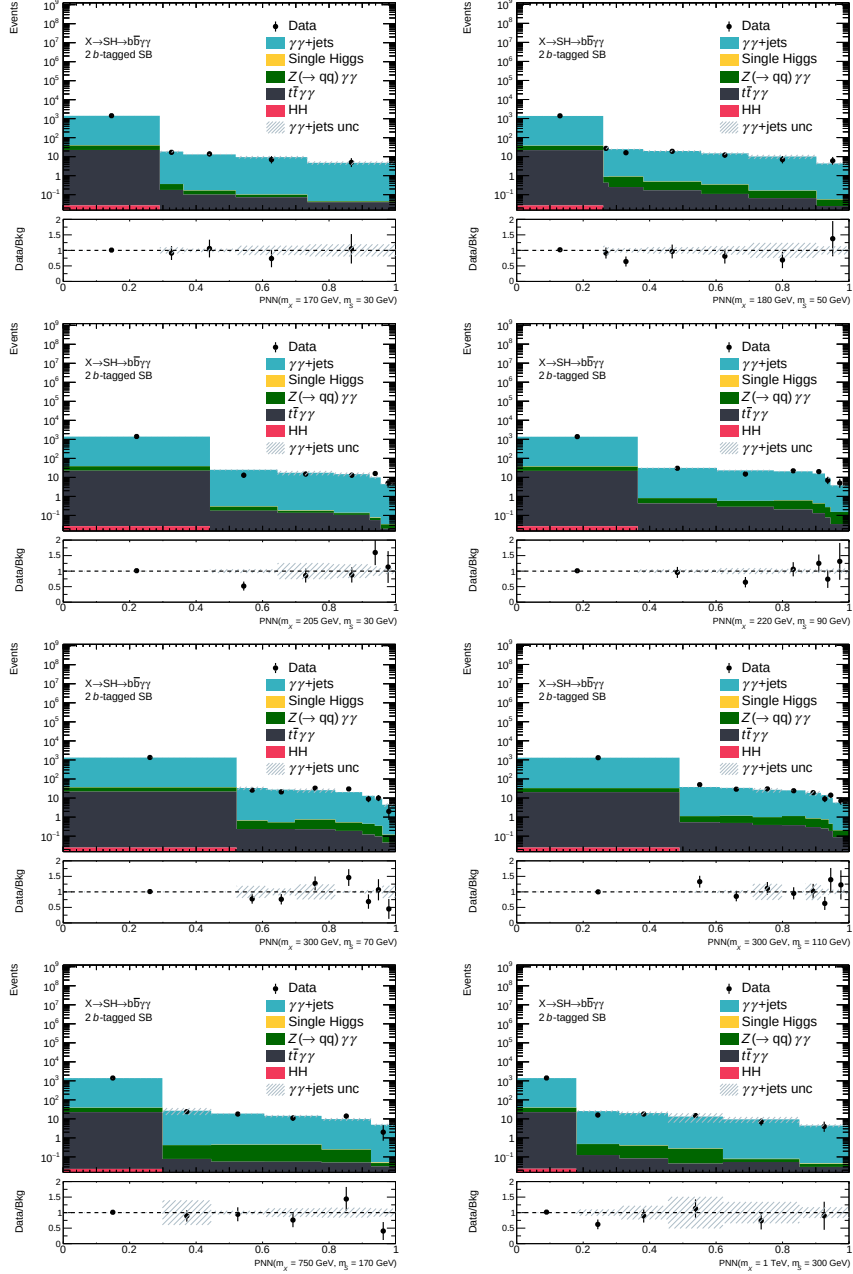


Fig. 7.18: Post-fit comparisons between data and simulations for the PNN score (m_X, m_S) in the $m_{\gamma\gamma}$ side-band region, following the 2 b -tagged selection. The calculation of the error bands is detailed in Section 7.6.

7.4.4.2 Merged Region

In the Merged Region, a 1 b -tagged selection is applied to both data and MC samples. Figures 7.19 and 7.20 illustrate the data-to-simulation comparison in the side-band for $m_{\gamma\gamma}$, $P_T^{b\text{-jet}}$, $m_{b\gamma\gamma}$, $m_{b\gamma\gamma}^*$, and PNN scores.

A normalization factor of 1.03 ± 0.01 , obtained from a fit to side-band data, is applied to the $\gamma\gamma$ +jets MC prediction. The normalization factors differ between the Resolved and Merged Regions. There are no measurements of the $\gamma\gamma$ process with jets or b -jets. The closest measurement is $\gamma\gamma$ +jets with Run 1 data [214]. In that study, the normalization factors for LO Sherpa (Pythia) are 1.4 (1.6) and 1.25 (2.6) for $N_j = 1$ and 2, respectively. The normalization factors for NLO GoSAM are 1.12 and 1.09 for $N_j = 1$ and 2, respectively. Differences in simulations can lead to varying normalization factors in this analysis.

Only the Sherpa $\gamma\gamma$ +jets MC prediction is needed for the QCD continuum background. There is no need to include γ -jets or dijet data-driven templates.

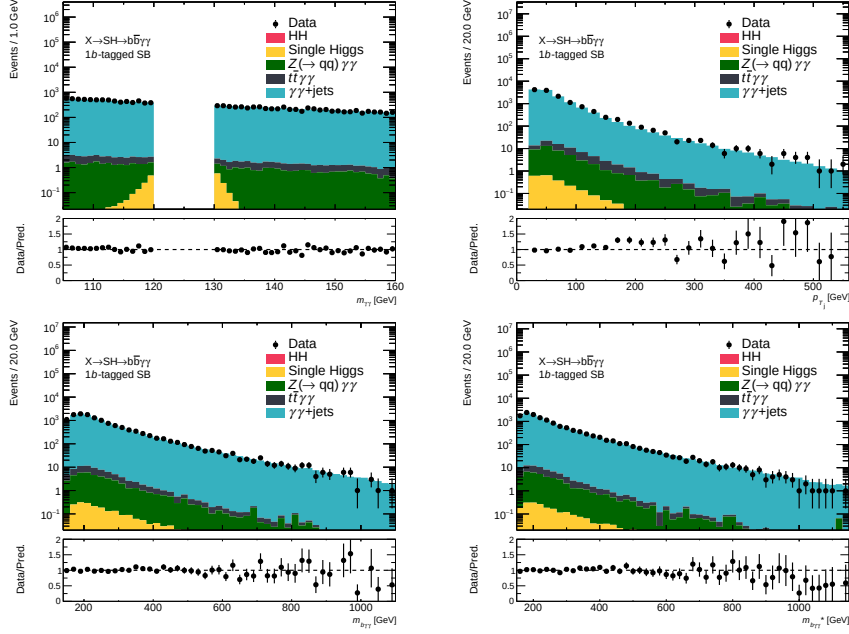


Fig. 7.19: Post-fit comparisons between data and simulation for the $m_{\gamma\gamma}$, $p_T^{b\text{-jet}}$, $m_{b\gamma\gamma}$, and $m_{b\gamma\gamma}^*$ distributions in the side-band region, following the 1 b -tagged selection.

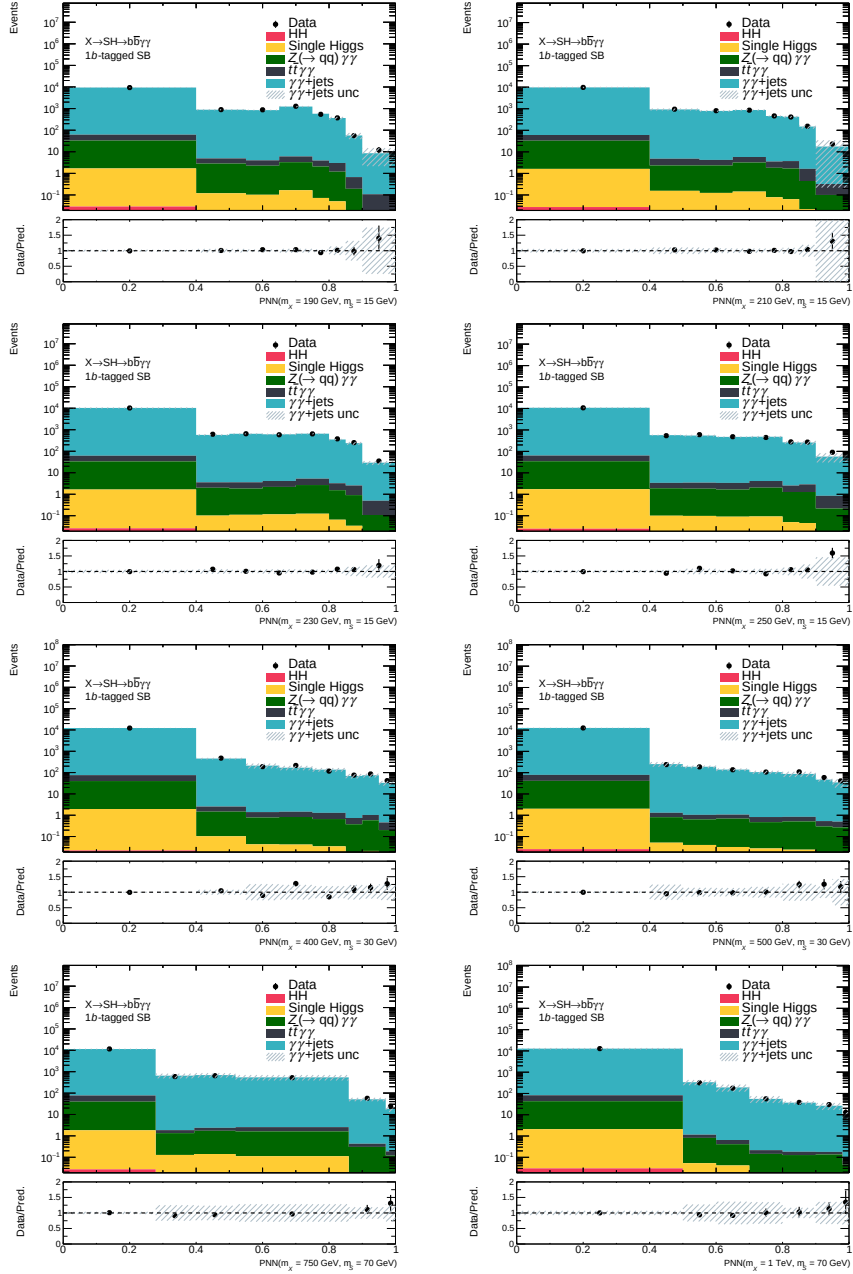


Fig. 7.20: Post-fit comparisons between data and simulation for the PNN score (m_X, m_S) in the $m_{\gamma\gamma}$ side-band region, following the 1 b -tagged selection. The method for calculating the error bands is outlined in Section 7.6.

7.5 Interpolation

To investigate signals for m_X and m_S values that were not originally simulated, two interpolation techniques are employed: one for the PNN score distribution to estimate shapes for any specified (m_X, m_S) values (termed shape interpolation) and another to estimate signal efficiencies (termed yield interpolation).

The parameterization of the PNN facilitates the exploration of any (m_X, m_S)

hypothesis by enabling direct interpolation of the background across the defined (m_X, m_S) parameter space. This approach is particularly effective in the extensive phase space encompassed by the 2 b-tagged region, where a comprehensive understanding of background behaviors is essential. As a result, optimized binning is required only for the interpolated background distributions, which are determined based on the predicted number of background events at high PNN scores and the corresponding signal-to-background ratios.

Appendix B.1.1 presents a comprehensive analysis of the interpolation methodologies utilized for signal shapes and yields, detailing the statistical techniques implemented to ensure precision. Appendix B.1.2 addresses the systematic uncertainties related to the interpolation process, providing insights into their potential effects on the analysis. Additionally, Appendix B.1.2.1 describes the signal injection tests performed to determine the optimal granularity required for scanning over (m_X, m_S) values, thereby strengthening the robustness of the interpolation framework.

The resultant 212 interpolated points are illustrated in Figure 7.21. Notably, the efficacy of Lorentz interpolation diminishes at certain edge points, where the computational assumptions may not hold. A comparative analysis of limits derived from Monte Carlo (MC) simulations versus interpolated limits indicates that interpolation maintains its reliability for $m_X \geq 300$ GeV and $m_S \geq 70$ GeV. To ensure the detection of any excess signals, 92 additional MC samples were generated and integrated into the final analysis, reinforcing the validity of the interpolated results.

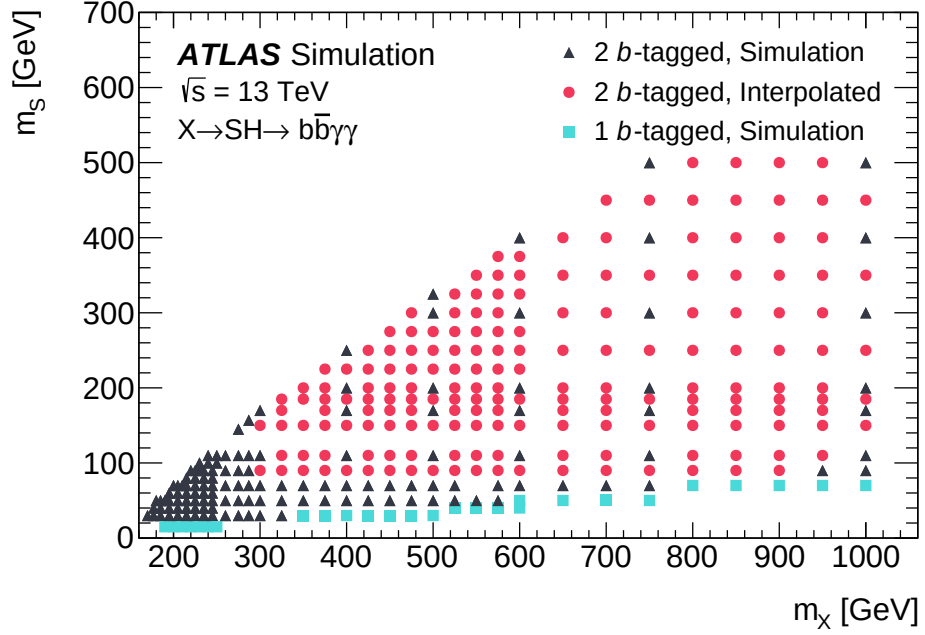


Fig. 7.21: The (m_X, m_S) signals utilized for significance and limit calculations are displayed. Simulated signals are indicated by black triangles and red squares, while limits for blue circle points are derived from interpolated PNN scores.

7.6 Systematics

7.6.1 Experimental Systematics

The experimental systematic uncertainties are evaluated using dedicated samples where each object that participates in the selection, reconstruction, and identification processes is shifted by its positive and negative 1σ variation. Multiple “schemes” are implemented to minimize the number of nuisance parameters:

- Luminosity: 0.83%, using the LUCID-2 detector for primary luminosity measurements, supplemented by measurements from the inner detector and calorimeters.
- Pile-up modelling,
- Diphoton trigger efficiency,
- Photon ID efficiency,
- Photon isolation efficiency,
- Photon energy scale (1 NP),
- Photon energy resolution (1 NP),
- Jet energy scale (CategoryReduction scheme),

- Jet energy resolution (FullJER scheme),
- Jet vertex tagger efficiency,
- Flavour tagging efficiencies (SF Eigen, Medium Reduction Scheme)

For the signal, the impact on the selection efficiency and shape is evaluated. For single and di-Higgs backgrounds, the impact on yield and shape is considered, while for continuous backgrounds, only the shape impact is considered.

The uncertainties associated with the normalization of backgrounds in both the 2 b -tagged and 1 b -tagged categories are detailed in Tables 7.15 and 7.17, respectively. Examples illustrating the impact on signal yields are presented in Tables 7.16 and 7.18. While all upward and downward variations were employed within the statistical framework, for clarity, these variations have been symmetrically combined and grouped into a quadrature sum for easier interpretation. For instance, the “ b -jet efficiency” accounts for the combined up and down variations of FT_EFF_Eigen_B_0, FT_EFF_Eigen_B_1, and FT_EFF_Eigen_B_2. The contributions from all backgrounds have been considered, with significant impact observed primarily in the major single-Higgs backgrounds (ttH , ZH , and ggH), due to their notable yield.

The experimental uncertainty for the VBF Higgs process was not computed, as its contribution was deemed negligible (constituting only a few percent of the single-Higgs background) and because it is already associated with a 100% theoretical uncertainty (similarly, the same rationale applies to WH). In the case of the $tHjb$ and bbH processes, their yields are similar; however, the theory uncertainty amounts to a few percent, comparable to the experimental one. Conversely, for the ggF process, we opted to calculate the experimental uncertainties despite its 100% theoretical uncertainty, as its contribution remains non-negligible.

In the merged-jet regime within the 1 b -tagged category, the same scale factors (SFs) and associated uncertainties applied to resolved jets are utilized. This approach was thoroughly discussed with the flavour-tagging conveners, who concurred that these SFs should be robust, particularly given that double- b jets undergo partial calibration in multi-jet environments due to the frequent occurrence of $g \rightarrow b\bar{b}$ splittings. The proximity of the overall SF to unity for a mixed sample—comprising both single- and double- b jets—supports the assumption that the SFs do not exhibit significant differences between the two cases. However, it was suggested that an increase in systematic uncertainties might be considered, though without a well-defined procedure, such an analysis falls outside the scope of this study.

Even when measuring b -tagging efficiency via the p_T^{rel} method using the MV2 algorithm, as recommended by the conveners, it was noted that “the optimal

Table. 7.15: Uncertainty [in %] on the background yields in the 2 b -tagged category.

Source	ttH	ZH	ggHH	ggH	ggZH	tHjb	VBFHH	Zqqyy	Zbbyy
Event-based									
Photon Trigger	1.01	1.02	1.00	1.04	0.98	1.03	1.02	1.00	1.25
Pile-up reweighting	0.88	0.76	0.56	0.43	0.60	0.99	0.60	3.69	1.15
Photon									
Photon Energy Resolution	0.42	0.42	0.34	0.42	0.43	0.63	0.43	2.79	0.78
Photon Energy Scale	0.17	0.18	0.12	0.07	0.11	0.18	0.24	14.53	0.90
Photon ID	1.59	1.61	1.44	1.64	1.49	1.60	1.59	1.72	1.96
Photon Isolation	1.55	1.57	1.45	1.60	1.46	1.59	1.59	1.27	1.88
Jet									
Jet Energy Scale	1.36	0.94	0.55	1.81	0.74	0.76	0.72	5.30	1.09
Jet Energy Resolution	7.33	4.60	2.91	7.50	3.36	4.88	3.08	0.68	5.37
Flavour-tagging									
b-jet efficiency	2.07	2.99	2.51	3.05	2.55	2.30	2.83	0.10	3.36
c-jet efficiency	0.40	0.71	0.06	1.68	0.60	0.92	0.07	13.12	0.22
light-jet efficiency	0.79	0.38	0.40	2.72	0.51	0.90	0.42	1.85	0.48

Table. 7.16: Uncertainty [in %] on the yield for several example signals in the 2 b -tagged category.

Source	X190 S50	X250 S110	X600 S170	X1000 S300
Event-based				
Photon Trigger	1.00	1.03	1.01	0.99
Pile-up reweighting	1.77	1.11	0.51	0.49
Photon				
Photon Energy Resolution	0.78	0.56	0.34	0.23
Photon Energy Scale	0.58	0.54	0.35	0.30
Photon ID	1.98	2.02	1.79	1.82
Photon Isolation	1.63	1.67	1.35	1.63
Jet				
Jet Energy Scale	4.24	1.20	0.43	0.43
Jet Energy Resolution	14.44	5.82	2.52	2.06
Flavour-tagging				
b-jet efficiency	4.95	3.68	2.22	2.13
c-jet efficiency	0.62	0.07	0.02	0.01
light-jet efficiency	1.43	0.39	0.48	0.54

Table. 7.17: Uncertainty [in %] on the background yields in the 1 b -tagged category.

Source	ttH	ZH	ggHH	ggH	ggZH	tHjb	VBFHH	Zqqyy	Zbbyy
Event-based									
Photon Trigger	1.01	1.02	1.00	1.00	1.01	1.06	1.01	1.39	1.07
Pile-up reweighting	0.75	0.44	0.49	0.34	0.36	0.91	0.51	1.04	0.77
Photon									
Photon Energy Resolution	0.45	0.46	0.36	0.46	0.36	0.39	0.41	0.93	0.98
Photon Energy Scale	0.21	0.19	0.16	0.19	0.18	0.32	0.11	1.82	1.43
Photon ID	1.60	1.65	1.47	1.65	1.52	1.64	1.60	2.08	1.84
Photon Isolation	1.57	1.61	1.47	1.60	1.50	1.61	1.57	2.02	1.74
Jet									
Jet Energy Scale	1.30	1.04	0.51	2.04	0.58	0.61	0.49	0.45	0.77
Jet Energy Resolution	5.23	4.91	2.88	8.17	3.01	3.06	2.64	4.00	4.37
Flavour-tagging									
b-jet efficiency	0.68	0.48	1.31	0.42	0.67	0.41	0.86	0.12	0.56
c-jet efficiency	0.32	1.59	0.05	2.19	1.45	0.15	0.07	4.03	0.03
light-jet efficiency	0.74	1.15	0.44	3.60	1.28	0.55	0.46	2.84	0.46

Table. 7.18: Uncertainty [in %] on the yield for several example signals in the 1 b -tagged category.

Source	X190 S15	X230 S15	X400 S30	X1000 S70
Event-based				
Photon Trigger	1.03	1.02	1.00	0.99
Pile-up reweighting	0.65	0.66	0.52	0.35
Photon				
Photon Energy Resolution	0.47	0.48	0.26	0.23
Photon Energy Scale	0.45	0.56	0.33	0.31
Photon ID	1.99	1.97	1.84	1.81
Photon Isolation	1.66	1.63	1.46	1.70
Jet				
Jet Energy Scale	1.32	0.92	0.65	0.35
Jet Energy Resolution	5.51	3.97	2.77	1.78
Flavour-tagging				
b-jet efficiency	1.57	1.21	0.61	0.64
c-jet efficiency	0.01	0.05	0.06	0.04
light-jet efficiency	0.55	0.52	0.53	0.60

approach would involve estimating the gluon splitting contribution directly from data and assigning a bin-by-bin statistical uncertainty comparable to that of other templates” [215]. According to supporting documentation [24], the fraction of gluon-splitting jets identified as b -jets ranges from a few percent at low p_T to approximately 20% at 200 GeV, as illustrated in Figure 7.22a. The p_T distribution of jets in the 1 b -tagged category is shown in Figure 7.22b.

It was also proposed to adopt a conservative approach, setting b -tagging uncertainties to 100%. However, under such an extreme assumption, the fits fail to converge. Furthermore, implementing a 50% prior uncertainty (approximately tenfold the current systematic uncertainties) would significantly broaden the confidence intervals, rendering the results impractical.

A bibliographic review on b -tagging in dense environments, particularly using the MV2c10 algorithm and data from 2015 and 2016 [216], examined b -tagging efficiency and SFs as a function of the minimum ΔR between the b -jet and the nearest jet. The findings indicated that SFs remain relatively constant, providing confidence that similar behavior should hold for merged jets. While b -tagging efficiency may differ between merged and resolved jets, there is no evidence to suggest a significant discrepancy in the data/MC efficiency ratio. Thus, no additional systematic uncertainty is introduced.

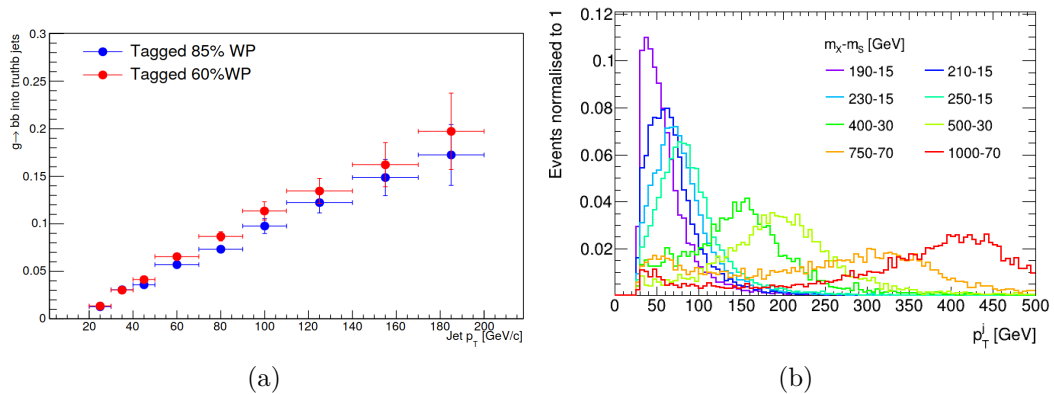


Fig. 7.22: (a) The fraction of gluon-splitting jets identified as bottom quarks as a function of jet transverse momentum, adapted from figure 20 of Ref. [24]; (b) Transverse momentum (p_T) distribution of b -tagged jets for the signal events in the 1 b -tagged category.

7.6.2 Theoretical Systematics

The theoretical uncertainties were calculated according to the guidelines set by the Physics and Modelling Group [217]. Systematic variations were computed dynamically to account for the following sources of uncertainty:

- **Scale Uncertainties:** These arise from variations in the renormalization and factorization scales, explored by varying the scales from 0.5 to 2 times the nominal value. This range is used to estimate theoretical uncertainties associated with higher-order perturbative QCD corrections. The envelope of the 7-point variations is used to extract asymmetric uncertainties, labeled as “QCD up” and “QCD down”.
- **PDF and α_s :** Uncertainties from Parton Distribution Functions (PDF) and the strong coupling constant (α_s) are evaluated. PDF variations are presented in Table 7.19, with α_s uncertainties combined in quadrature.
- **Parton shower/generator:** Theoretical uncertainties due to parton shower and generator modelling are assessed by comparing Pythia and Herwig for both the signal and resonant background processes. For the continuum background, comparisons were made between Sherpa and MadGraph interfaced with Pythia [218].

Table. 7.19: PDF sets and their corresponding variations used for the different signal and background processes.

Sample	LHAPDF	PDF set	α_s	Alternative PDF	Prescription
<i>SH</i> Signal	247000	NNPDF23_lo_as_0130_qed 100 variations	0.130–0.119	CT14llo MMHT2014lo68cl	std deviation
Sherpa $\gamma\gamma$ +jets	621001	NNPDF30_nlo_as0118 100 variations	0.117–0.119	MMHT2014nnlo68cl CT14nnlo PDF4LHC15_nnlo_30	std deviation
ZH/ttH/HH	90400	PDF4LHC15_nlo_30_pdfas 30 variations	0.117–0.119		symmetric hessian
Z (qq) $\gamma\gamma$	303200	NNPDF30_nnlo_as_0118_hessian 100 variations	0.117–0.119	CT14nnlo MMHT2014nnlo68cl	symmetric hessian

7.6.3 Signal

The baseline PDF used is the NNPDF23_lo_as_0130_qed set, with the standard deviation from 100 variations taken as the PDF uncertainty. The strong coupling constant, α_s , is varied between 0.119 and 0.130, and both uncertainties are combined in quadrature to estimate the total uncertainty. Additionally, comparisons with the CT14llo and MMHT2014lo68cl PDF sets, as recommended by the Physics Modelling Group (PMG), account for further uncertainties. Examples of the impact on the PNN score distributions are presented in Figure 7.23, covering two cases in the 2 b -tagged category and one in the 1 b -tagged category. The uncertainties remain relatively flat across the PNN score, with total PDF and α_s uncertainties increasing with m_X , ranging from 3% to 10% at the TeV scale.

Signal generation uses Pythia, and modifications to the parton shower are not feasible. For the $X \rightarrow HH \rightarrow b\bar{b}\gamma\gamma$ samples [25], MadGraph is used with Pythia

for showering, and Herwig for $m_X = 280, 500, \text{ and } 1000 \text{ GeV}$ with $m_S = 125 \text{ GeV}$.

PNN distributions for these mass points, shown in Figure 7.25, reveal distribution ratios between 0.8 and 1.2 across the full range, and between 0.9 and 1.1 for PNN scores above 0.7, where most signal events are concentrated. As a result, a global normalization uncertainty of 10% is applied to the signal.

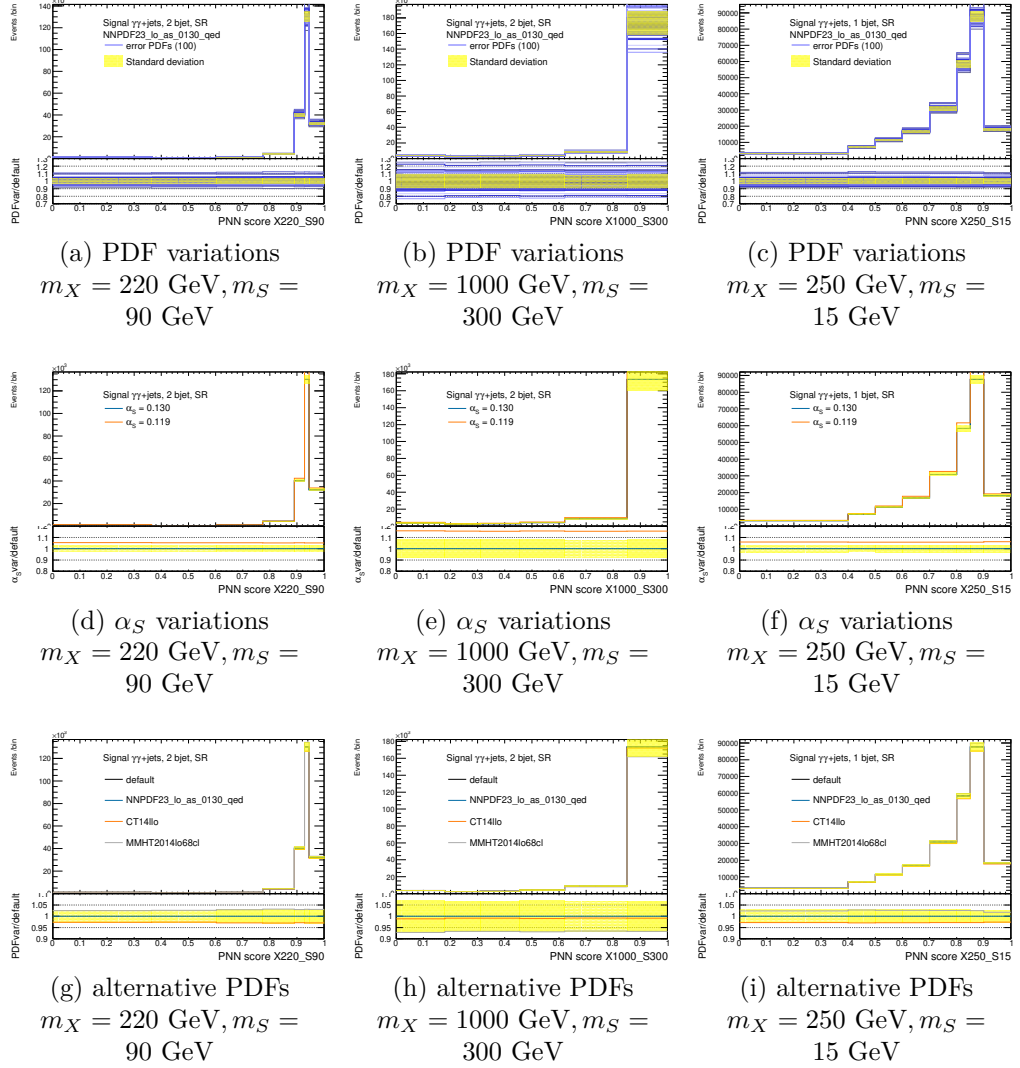


Fig. 7.23: Uncertainties on the PNN score for the signal due to QCD scales (top), the 100 PDF variations shown in blue and their standard deviation in yellow (middle), and alternative PDFs (bottom). These are presented for $m_X = 220 \text{ GeV}, m_S = 90 \text{ GeV}$ (left), $m_X = 1000 \text{ GeV}, m_S = 300 \text{ GeV}$ (middle), and $m_X = 250 \text{ GeV}, m_S = 15 \text{ GeV}$ (right).

7.6.4 Continuum Diphoton Background

For the continuum diphoton background, uncertainties are primarily driven by shape variations from renormalization and factorization scale changes. The baseline PDF is NNPDF30_nnlo_as_0118, with α_S varied between 0.117 and

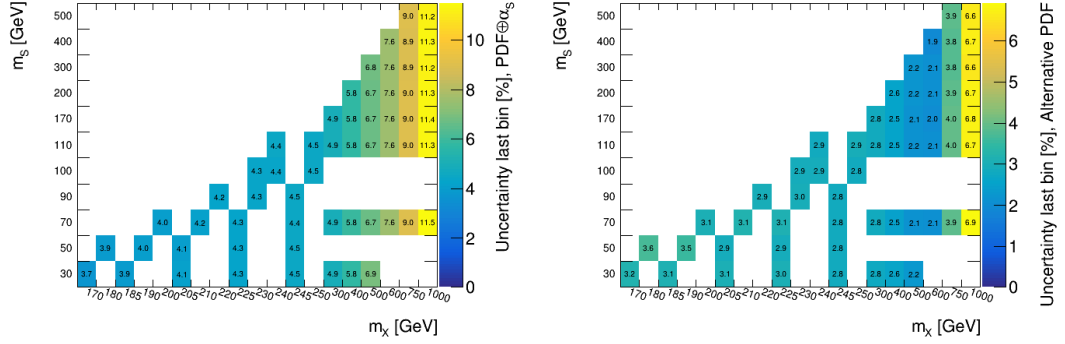


Fig. 7.24: The value of the $\text{PDF} \oplus \alpha_S$ uncertainty (left) and Alternative PDFs uncertainty (right) in the last bin of the PNN score for all signal points in the 2 b -tagged category.

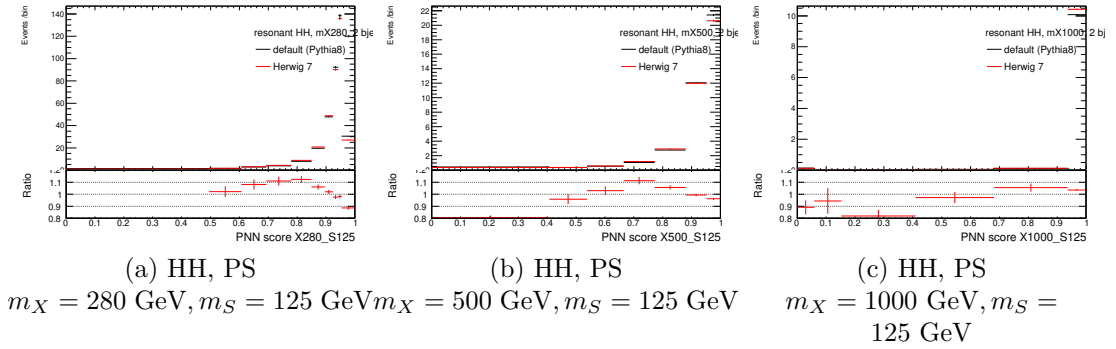


Fig. 7.25: Parton shower variations comparing MadGraph + Pythia8 and MadGraph + Herwig7 on the PNN score for $m_X = 280 \text{ GeV}, m_S = 125 \text{ GeV}$ (left), $m_X = 500 \text{ GeV}, m_S = 125 \text{ GeV}$ (middle), and $m_X = 1000 \text{ GeV}, m_S = 125 \text{ GeV}$ (right) for the resonant HH process.

0.119. While generally small, these uncertainties become more pronounced at higher masses. Parton shower comparisons (Sherpa vs. MadGraph + Pythia) are included to account for potential systematic differences. Due to the low event yield, these uncertainties have a minimal effect on the overall analysis.

Theoretical uncertainties are evaluated by interpolating between the Side Bands (SB) and Signal Region (SR), computed as the uncertainties on the SR/SB ratio using Sherpa. Combined uncertainties for QCD, PDF+ α_S , and modelling are 0.1%, 0.02%, and 1.9% for the 1 b -tagged category, and 0.3%, 0.07%, and 6.6% for the 2 b -tagged category. These are added in quadrature, yielding total uncertainties of 1.9% and 6.6%, respectively.

7.6.5 Resonant Backgrounds (Single-Higgs and HH)

Both normalization and shape uncertainties are applied to various single-Higgs and di-Higgs backgrounds. A 100% global uncertainty is used for ggF, VBF, and WH processes, motivated by heavy-flavor production studies involving b -jets, especially in association with top-quark pairs and W bosons [218, 219]. For ttH and ZH, heavy-flavor production is included at LO, and scale and PDF uncertainties are evaluated per PMG guidelines, using PDF4LHC15 with Hessian errors from 30 variations. Parton shower uncertainties are estimated by comparing Powheg+Pythia8 with Powheg+Herwig7. QCD, PDF, and parton shower uncertainties typically reach a few percent, up to 10% in some bins, with PDF and α_S uncertainties remaining flat across the PNN score.

Inclusive cross-section uncertainties from Yellow Report 4 [220] are applied to smaller single-Higgs backgrounds, with QCD scale and PDF+ α_S uncertainties for the ggHH process [221]. These uncertainties stem from renormalization scheme and top-quark mass scale variations [222] and cannot be recalculated. The results are summarized in Table 7.20. No merging uncertainties between Powheg and MadGraph are included, per PMG recommendations [217].

7.6.6 $Z (\rightarrow qq)\gamma\gamma$ Background

The $Z \rightarrow qq$ and $Z \rightarrow b\bar{b}\gamma\gamma$ backgrounds are treated analogously to other processes, with uncertainties derived from QCD scale and PDF variations. While these uncertainties can be substantial in specific bins, their overall effect on the total yield is minimal due to the low expected event rate. The detailed uncertainty evaluation across various backgrounds ensures a precise estimation of the total systematic uncertainty.

Table. 7.20: Inclusive theoretical uncertainty [in %] on the cross-sections for the single-Higgs backgrounds (excluding ttH and $qq \rightarrow ZH$) and the di-Higgs backgrounds.

	QCD Scale	PDF+ α_S
ggH	100 %	
VBF	100 %	
WH	100 %	
gg $\rightarrow$ ZH	+25.1% -18.9%	2.4 %
bbH	+20.2% -23.9%	
tHbj	+2.4% -1.8%	2.2 %
tHW	+4.9% -6.7%	6.3 %
ggHH	(+ m_{top} unc.) +6% -23%	3 %
VBFHH	0.03+% -0.04%	2.1%

7.6.7 Interpolation of the Systematic Uncertainties

Systematic uncertainties for the background processes do not require interpolation. Given that the PNN score can be computed for any value of m_S and m_X , the corresponding systematic uncertainties can also be directly computed for any point. However, for the signal processes, both theoretical and experimental uncertainties need to be interpolated. It was established in previous sections that these systematic uncertainties depend on the PNN score. For interpolation purposes, only the value in the last bin of the PNN score (the most sensitive one where the majority of the signal resides) is used, assuming a flat uncertainty. Validation of this assumption will be demonstrated in this subsection.

7.6.7.1 Interpolation of Signal Theoretical Systematics

As illustrated in Figure 7.23, systematic uncertainties from the PDF and α_S variations are relatively flat. This flatness justifies using the value from the last bin for interpolation purposes. All values presented in Figure 7.24 are input into a TGraph2D object, allowing the computation of systematic uncertainties for any point in the m_S - m_X plane.

7.6.7.2 Interpolation of Signal Experimental Systematics

To validate the use of the uncertainty value in the last PNN bin, a closure test is performed: for points where MC samples exist, the systematic uncertainty in the last bin for each MC point is extracted, and the nominal histograms are rescaled using this value. Another check involves ensuring that the interpolation from the

TGraph2D histograms works as intended. For this, in the interpolation of nominal yields, MC points are sequentially removed, and the difference between the default and interpolated uncertainties is computed. It is found that the interpolated values are within 1% of the default ones for both low- m_X and high- m_X regions.

7.6.8 Summary and Impact of the Systematic Uncertainties

The systematic uncertainties accounted for include shape uncertainties such as QCD scales and PDFs for ttH , ZH , and $\gamma\gamma$ +jets, as well as PDF-set and modelling uncertainties for $\gamma\gamma$ +jets, parton shower uncertainties for HH , ttH , ZH , and all experimental systematics described in Section 7.6.1. All included systematic uncertainties are summarized in Table 7.21. Normalization systematics encompass a 99.9% uncertainty on the ggH , $VBFH$, and WH backgrounds, a 0.83% uncertainty on the integrated luminosity, and uncertainties related to the extrapolation of $\gamma\gamma$ +jets normalization from the control region (CR) to the signal region (SR). These uncertainties affect only the SR. A slight constraint on the diphoton modelling is noted, as the Asimov dataset was generated with Sherpa MC, while the primary uncertainty arises from the difference between Sherpa and MadGraph.

The comparison between data and simulation for the PNN score distributions within the $m_{\gamma\gamma}$ sidebands, which incorporates both theoretical and experimental uncertainties, is illustrated in Figure 7.26. All experimental sources are combined in quadrature, a method that appears reasonable given the correlation matrices observed in Figures B.9 and B.10 in Appendix B.2 as an example in the 2 b tagged region. The systematic uncertainties effectively account for the observed discrepancies between data and simulation.

The influence of systematic uncertainties is discussed in Tables B.2 as an example, highlighted by the ranking plots in Section 7.6.1. The most significant source of uncertainty arises from the modelling uncertainty of the Sherpa $\gamma\gamma$ +jets process, where pre-fit uncertainties occasionally exceed 100% (the post-fit uncertainties are currently constrained due to the use of Asimov data based on the Sherpa MC). Subsequently, the MC statistical uncertainties, along with other theoretical uncertainties related to the Sherpa $\gamma\gamma$ +jets sample, contribute to a few percent. Comparatively, the uncertainties associated with single-Higgs and di-Higgs processes have a considerably smaller impact on the expected limits.

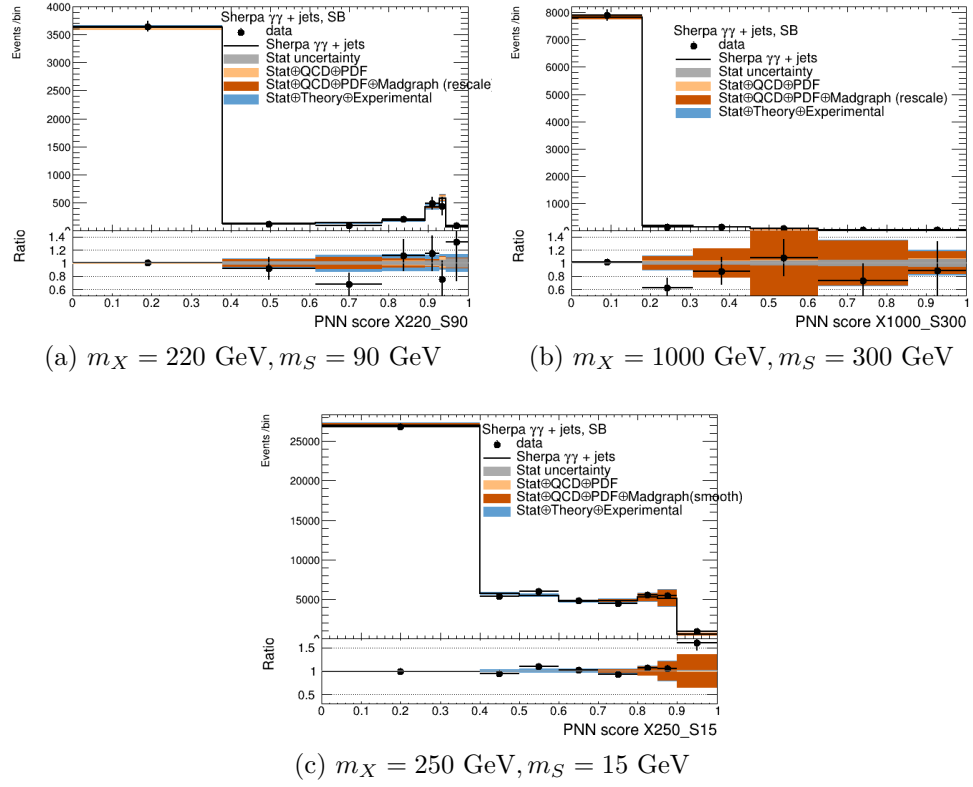


Fig. 7.26: Comparison between data and simulation for the PNN score distributions for (a) $m_X = 220 \text{ GeV}, m_S = 90 \text{ GeV}$, (b) $m_X = 1000 \text{ GeV}, m_S = 530 \text{ GeV}$, and (c) $m_X = 250 \text{ GeV}, m_S = 15 \text{ GeV}$ in the $m_{\gamma\gamma}$ side-bands, including statistical, theoretical, and experimental uncertainties.

Table. 7.21: A summary of the systematic uncertainties incorporated in the final results. For the continuum background, as its normalization is derived from the data sideband, “Shape+Normalization” systematics should be interpreted as “Shape only”.

		Signal	HH ggF	HH VBF	ttH and ZH	Other Single Higgs	Continuum $\gamma\gamma$ +jets
Theory	Normalization	$BR(H \rightarrow \gamma\gamma)$	$BR(H \rightarrow \gamma\gamma)$ $BR(H \rightarrow b\bar{b})$ PDF+ α_S Scales + m_t	$BR(H \rightarrow \gamma\gamma)$ $BR(H \rightarrow b\bar{b})$ PDF+ α_S Scales	$BR(H \rightarrow \gamma\gamma)$	$BR(H \rightarrow \gamma\gamma)$ PDF+ α_S Scales	$\gamma\gamma$ transfer factor
	Shape+Norm.	Scales, PDF+ α_S Parton shower Interpolation	Parton Shower		Scales, PDF+ α_S Parton Shower		Scales, PDF+ α_S Modelling
Exp.	Shape+Norm.	Pile-up modelling Diphoton trigger efficiency Photon identification and isolation efficiency Photon energy scale and resolution Jet energy scale and resolution Jet vertex tagger efficiency Flavour tagging efficiency (all exp. systematics are neglected for $b\bar{b}H$, tH and $VBF H$)					

7.7 Results

7.7.1 Statistical model

The statistical analysis is based on a likelihood function L , which is formulated as the product of the Poisson probabilities across all bins within the signal region and the sidebands, further constrained by systematic uncertainties. Mathematically, the likelihood is expressed as [223, 224]:

$$\begin{aligned}
 L(\mathbf{n}, \boldsymbol{\theta}^0 \mid \mu_{\text{sig}}, \boldsymbol{\mu}_p, \boldsymbol{\theta}) &= \mathcal{P}_{\text{SR}} \times \mathcal{P}_{\text{SB}} \times \mathcal{C}_{\text{syst}} \\
 &= \prod_{i \in \text{SR}} \mathcal{P}(n_i \mid \lambda_i(\mu_{\text{sig}}, \boldsymbol{\mu}_p, \boldsymbol{\theta})) \times \prod_{i \in \text{SB}} \mathcal{P}(n_i \mid \lambda_i(\mu_{\text{sig}}, \boldsymbol{\mu}_p, \boldsymbol{\theta})) \times \mathcal{C}_{\text{syst}}(\boldsymbol{\theta}^0, \boldsymbol{\theta}),
 \end{aligned} \tag{7.2}$$

Here, $\mathcal{P}_{\text{SR}}$ and $\mathcal{P}_{\text{SB}}$ represent the Poisson terms for the signal region and the sidebands, respectively. These terms depend on the observed number of events n_i in each bin i and their expected values λ_i , which are functions of the fit parameters: the signal strength μ_{sig} , the background normalization factors $\boldsymbol{\mu}_p$, and the nuisance parameters $\boldsymbol{\theta}$ that account for systematic uncertainties.

Based on this likelihood, a test statistic for μ_{sig} can be derived [225]:

$$\tilde{t}_\mu = -2 \ln \frac{L(\mu, \hat{\boldsymbol{\theta}}(\mu))}{L(\hat{\mu}, \hat{\boldsymbol{\theta}})}. \tag{7.3}$$

This test statistic quantifies the level of disagreement between the observed data and the expectations. The p-value is then calculated to measure this disagreement. To assess the exclusion of a signal hypothesis, the CL_s method is

applied, using the asymptotic approximation as outlined in Ref. [225]:

$$\text{CL}_s = \frac{\text{CL}_{s+b}}{\text{CL}_b} = \frac{p_{s+b}}{1 - p_b}. \quad (7.4)$$

Here, p_i denotes the p-value for a given hypothesis i , where i represents either the signal-plus-background scenario ($s+b$) or the background-only scenario (b). A signal hypothesis is considered excluded at the 95% confidence level when $\text{CL}_s < 0.05$. The statistical fits are carried out separately for each signal region and its corresponding sideband.

The upper limit on the cross-section is defined as the maximum value a signal can achieve before it is excluded at the 95% confidence level ($\text{CL}_s < 0.05$). To determine this upper limit, a scan over μ_{sig} is performed, with a hypothesis test conducted iteratively for each value of μ_{sig} within the scanning range.

7.7.2 Blinded results

The following results are derived from the analysis using Asimov data.

The expected limits were compared between the 1 b -tagged and 2 b -tagged categories for certain mass points, specifically those with events present in both categories, as illustrated in Figure 7.3. These limits are detailed in Table 7.22. In categories where the fraction of events is below a few percent (e.g., $m_S = 15$ GeV in the 2 b -tagged category), limits cannot be computed due to insufficient signal events available for fitting. It is observed that when the fraction of events in the 1 b -tagged category exceeds 50%, the limits are 2 to 6 times more stringent in comparison to the 2 b -tagged category. Consequently, it was decided to consider only the limits from the 1 b -tagged category for these specific mass points, namely $m_S = 15$ GeV and $m_X, m_S = (400, 30), (500, 30), (600, 40), (750, 50), (1000, 70)$ GeV, particularly when $m_S/m_X \lesssim 0.09$, without combining the limits from the other category.

Table. 7.22: The expected 95% CL limit in the two categories is presented, with theoretical uncertainties taken into account (excluding experimental uncertainties at this stage).

$m_X_m_S$	Limit [fb] in 1 b -tagged category	Limit [fb] in 2 b -tagged category	Fraction in 1 b -tagged category
X400_S30	1.09	2.54	80%
X500_S30	0.72	~ 5	95%
X750_S70	0.45	0.26	32%
X1000_S500	0.19	0.43	69%

Figure 7.28 presents the expected limits on the signal production cross section, incorporating points from both the 1 b -tagged and 2 b -tagged regions.

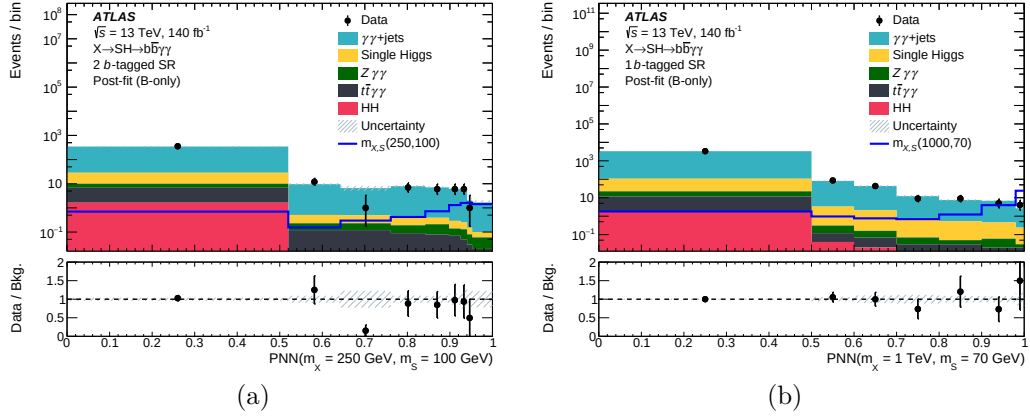
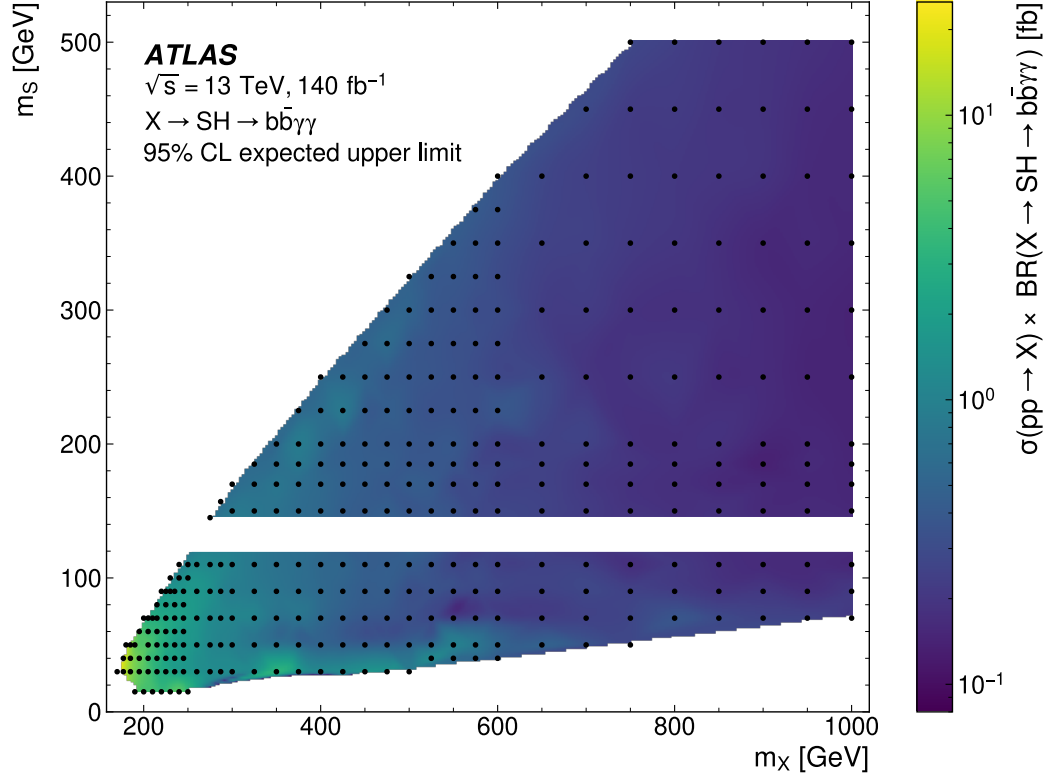


Fig. 7.27: Post-fit distributions of the PNN discriminant output are presented for (a) the 2 b -tagged signal region with $m_X = 250 \text{ GeV}$ and $m_S = 100 \text{ GeV}$, and (b) the 1 b -tagged signal region with $m_X = 1000 \text{ GeV}$ and $m_S = 70 \text{ GeV}$, following a background-only fit to the data. The signals for the two PNN parameterizations, normalized to a 1 fb cross section, are displayed for comparison. The $\gamma\gamma + \text{jets}$ category encompasses the combined contributions from $\gamma\gamma + \text{jets}$, $\gamma + \text{jets}$, and dijet backgrounds. The shaded error band indicates the total systematic uncertainty after the fit.

Distribution of PNN ($m_X = 250 \text{ GeV}$, $m_S = 100 \text{ GeV}$) and PNN ($m_X = 1000 \text{ GeV}$, $m_S = 70 \text{ GeV}$) in the SR after a background only fit are shown in Figure 7.27.

The corresponding Diagnostic plots in Appendix B.2 for the maximum likelihood fit of m_X , $m_S = (250, 100) \text{ GeV}$ in 2 b -jet category and m_X , $m_S = (1000, 70)$ are displayed in Figures B.11, B.12, B.9 and B.10. The impact, as illustrated in Figures B.11 and B.12, with corresponding numerical values provided in Tables B.2 and B.3, is quantified as the variation in the fitted parameter of interest (POI) when a nuisance parameter (NP) is shifted by one standard deviation.

The expected limit for $m_S = 125 \text{ GeV}$ is compared with the results from the resonant HH search reported in Ref. [25], as shown in Figure 7.29. The comparison reveals that the previous analysis yields better expected limits, which can be attributed to the optimized BDT selection for each mass point in Ref. [25]. However, despite extensive efforts, it was not possible to interpolate the limits between mass points in the previous analysis. During the review process, one reviewer highlighted gaps in the coverage of mass points at $m_X = 650, 750$, and 850 GeV . As a result, new MC samples were requested, and the entire optimization process and fits had to be redone. This experience motivated the current analysis to enable interpolation to any mass point, even with a slight reduction in expected sensitivity. Nonetheless, it was decided not to include the observed



(a)

Fig. 7.28: The expected 95% CL upper limits on the signal cross section times branching fraction for the $X \rightarrow SH$ process are shown in the (m_X, m_S) plane. The points represent the locations where the limits were evaluated. The band at $m_S = 125 \text{ GeV}$ is excluded, as those points correspond to regions already investigated in Ref.[25].

limits and significance for the points with $m_S = 125 \text{ GeV}$.

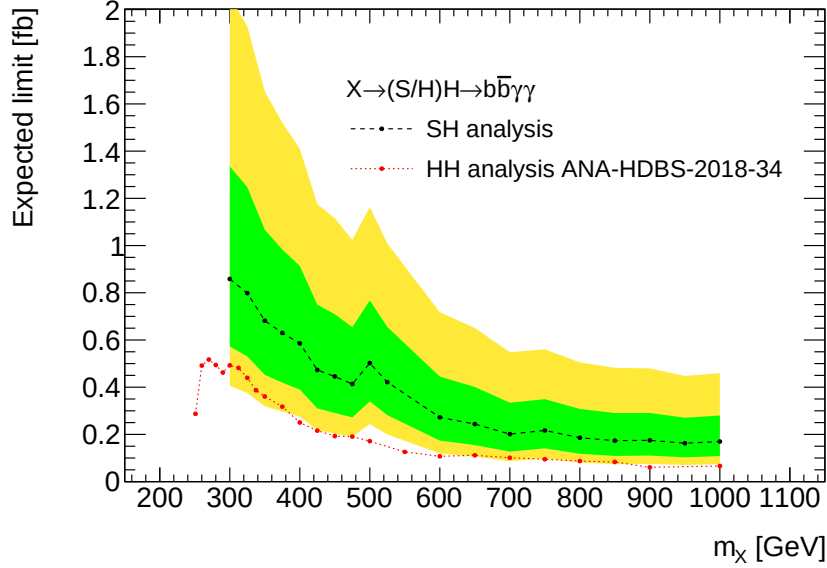


Fig. 7.29: The expected limits on the signal cross-section as a function of m_X for $m_S = 125$ GeV are shown for this analysis (in black) and compared to those from the analysis in Ref. [25] (in red).

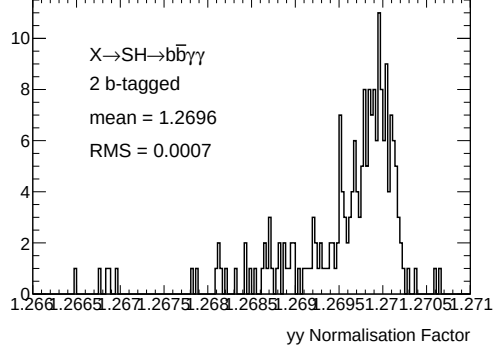
7.7.3 Unblinded results

The Normalisation Factors are recalculated for each data point. Their distributions are illustrated in Figures 7.30a and 7.30b for the 2 b -tagged and 1 b -tagged categories, respectively. The Root Mean Square (RMS) values are relatively small when compared to the uncertainty derived from the fits, which are approximately 0.03 and 0.01 for the two categories, respectively. Additionally, Figures 7.30c and 7.30d indicate no evident mass dependence in the Normalisation Factors.

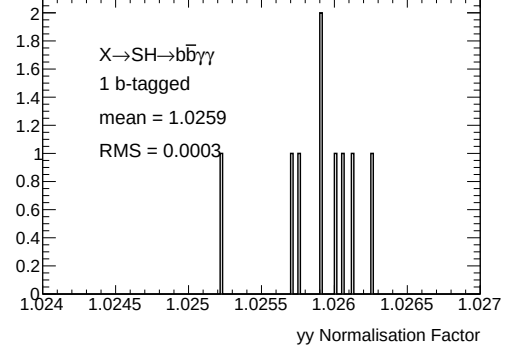
Figure 7.31 presents the observed limits on the signal production cross-section, incorporating both the 1 b -tagged and 2 b -tagged regions as well as interpolated points. Figure 7.32 illustrates the observed local significance for potential signal detection. A noticeable excess is identified in the region around $m_X = 575$ GeV and $m_S = 200$ GeV, showing a local significance of 3.55σ , with multiple adjacent points exhibiting an observed significance above 2.5σ .

CMS has reported an excess on $m_X, m_S = (650, 90)$ GeV with a local significance $Z_0 = 3.8$. The post-fit distribution for key PNN distributions is displayed in Figures B.14 in Appendix B.3. This point is evaluated using an interpolated signal template in our analysis and a local significance of $Z_0 = 0$ is found. As a cross check, the results with a simulated $m_X, m_S = (650, 90)$ GeV have also been computed. The unblinded results obtained with interpolated and MC signal templates are shown in table 7.23. No excess is found for any of the fits.

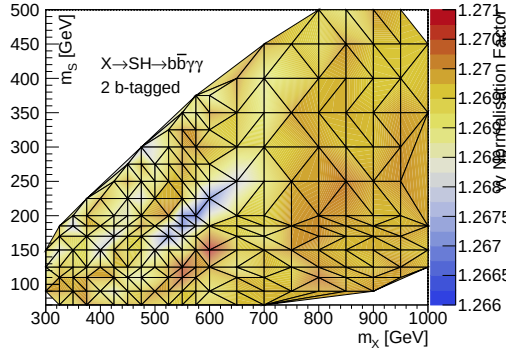
The pull plots for $(m_X, m_S) = (250, 110)$ GeV and $(m_X, m_S) = (1000, 70)$ GeV as examples are illustrated in Figures B.16 and B.17 in Appendix B.3.



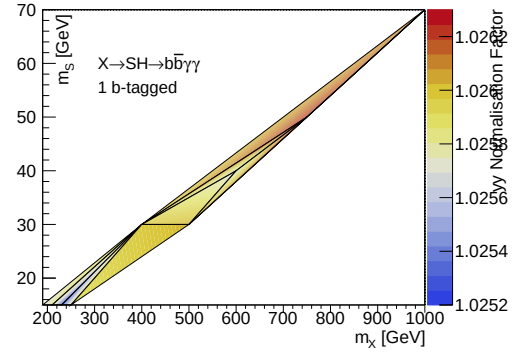
(a)



(b)



(c)

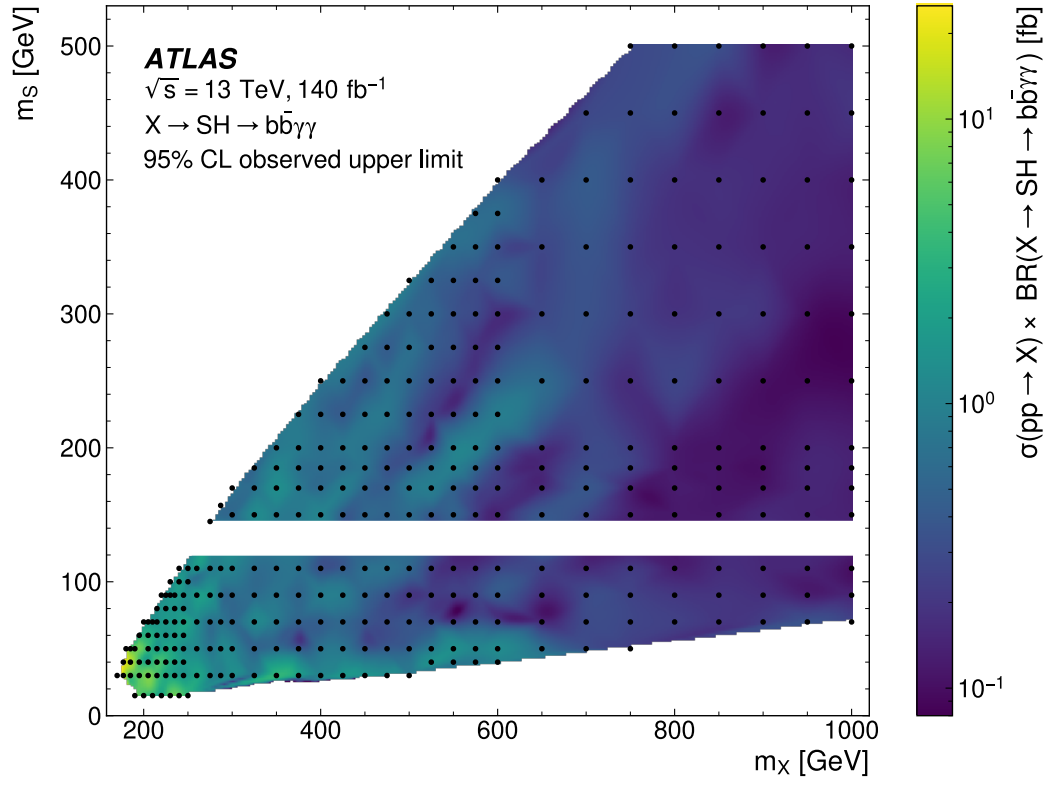


(d)

Fig. 7.30: Distribution of the Normalisation Factors for each point of the (a) 2 b -tagged and (b) 1 b -tagged categories. Normalisation Factors as a function of m_S and m_X of the (c) 2 b -tagged and (d) 1 b -tagged categories.

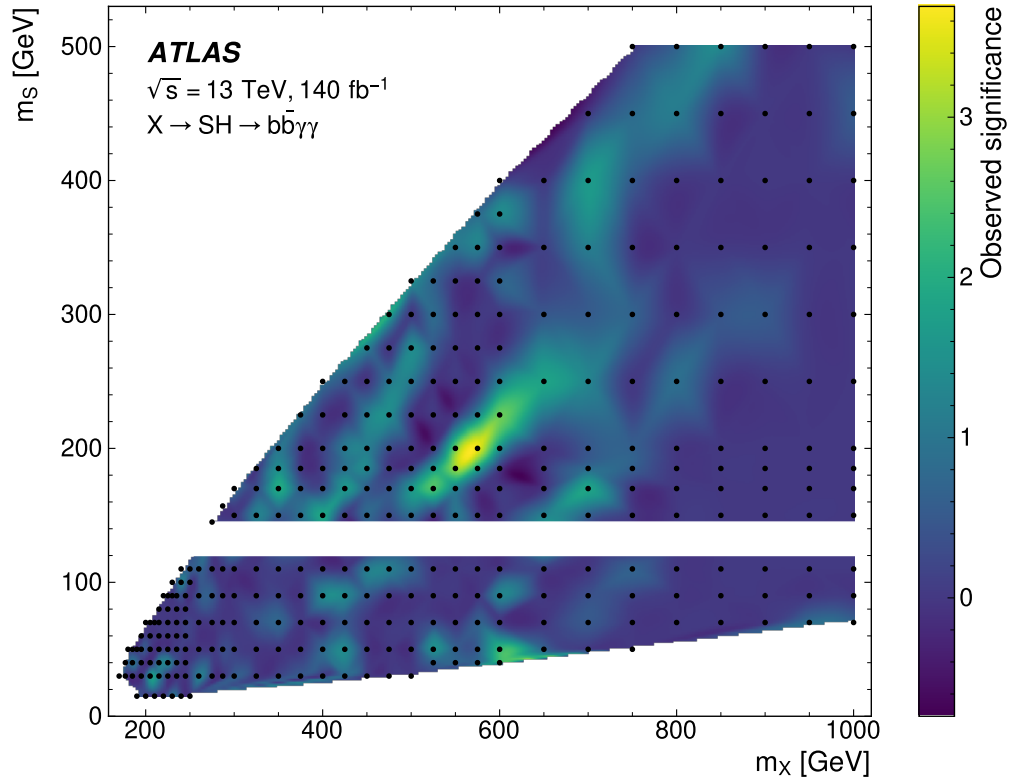
Table. 7.23: Comparison of the unblinded results on $m_X, m_S = (650, 90)$ GeV when using interpolated or MC signal templates.

Signal template	mX	mS	p0	Z0	observed	-2	-1	expected	1	2
Interpolated	650	90	0.5	0.00	0.172	0.113	0.163	0.253	0.414	0.673
MC	650	90	0.5	0.00	0.142	0.094	0.135	0.211	0.345	0.559



(a)

Fig. 7.31: Observed 95% CL upper limits on the signal cross section times branching fraction for the $X \rightarrow SH$ signal, in the (m_X, m_S) plane. The points show where the limits were evaluated. The band at $m_S = 125$ GeV is not shown as those points are equivalent to those already probed in Ref. [25]



(a)

Fig. 7.32: The local observed significance for signal discovery is shown for various $m_{X,S}$ signals in (a) the low m_X region and (b) the high m_X region.

7.7.4 Global Significance

Experiments aimed at uncovering new physics typically involve searching for signals across a continuous parameter space. To quantify the significance of a local deviation from the background-only hypothesis in terms of a p -value, one must consider the likelihood of such a fluctuation arising anywhere within the search domain. This is known as the “look-elsewhere effect”. In the context of varying the masses of two resonances, X and S , during the search for a $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ signal, an excess over the expected background was observed near $(m_X, m_S) = (575, 200)\text{GeV}$, with a local significance of 3.55σ . To correct for the “look-elsewhere effect”, the global significance must be determined. The global significance accounts for the probability of observing such a deviation anywhere in the search region under the background-only hypothesis:

$$\text{Global } p_0 = \mathbb{P}(\max_{\theta \in \mathcal{M}} q(\theta) > q_{obs} | \mu = 0) \quad (7.5)$$

where:

- θ represents the parameter being tested in the search. For the $SH \rightarrow b\bar{b}\gamma\gamma$ analysis, θ corresponds to the resonance masses m_X and m_S .
- $\mathcal{M}$ denotes the search range, which, in the $SH \rightarrow b\bar{b}\gamma\gamma$ analysis, is the two-dimensional grid of (m_X, m_S) mass points tested.
- q_θ is the test statistic used for the analysis, dependent on the specific signal parameter θ .
- q_{obs} is the observed maximum value of the test statistic across the entire search region.
- μ denotes the signal strength, with the probability evaluated under the background-only hypothesis, where $\mu = 0$.

The global p_0 is evaluated using the asymptotic method described in [226], which can be summarized as follows:

- The set of search parameters θ for which the test statistic $q(\theta)$ exceeds a defined threshold u is referred to as the excursion set:

$$A_u = \theta : q(\theta) > u \quad (7.6)$$

- It can be shown that the expected value of the “Euler characteristic” of the excursion set, denoted as $\phi(A_u)$, approaches the global p_0 under the null

hypothesis for sufficiently large values of u :

$$\mathbb{E}[\phi(A_u)] \approx \mathbb{P}\left(\max_{\theta \in \mathcal{M}} q(\theta) > u, \mid, \mu = 0\right) \quad (7.7)$$

Thus, evaluating the Euler characteristic $\phi(A_u)$ at the threshold $u = q_{obs}$ gives the global p_0 .

- Additionally, under the background-only hypothesis and for a two-dimensional search space, the expected Euler characteristic $\phi(A_u)$ follows this relation:

$$\mathbb{E}[\phi(A_u)] = \mathbb{P}(\chi^2 > u) + e^{-u/2} \cdot (\mathcal{N}_1 + \sqrt{u} \cdot \mathcal{N}_2) \quad (7.8)$$

where the constants $\mathcal{N}_1$ and $\mathcal{N}_2$ remain invariant across all thresholds u .

- In principle, convenient thresholds u can be used to evaluate the Euler characteristics $\phi(A_u)$, and by inverting Equation 7.8, the constants $\mathcal{N}_1$ and $\mathcal{N}_2$ can be extracted. Once determined, these values can be used in Equation 7.8 along with Equation 7.7 to compute the global p_0 as a function of the maximum test statistic. Setting $u = q_{obs}$ then yields the observed global p_0 .

To reduce the statistical uncertainty in the determination of $\mathcal{N}_1$ and $\mathcal{N}_2$, it is advised to generate a limited number of background-only toy datasets to evaluate the Euler characteristics at selected thresholds u . For a given threshold u , the expectation value of the Euler characteristic $\mathbb{E}(\phi(A_u))$ can be computed for each toy. The extraction of $\mathcal{N}_1$ and $\mathcal{N}_2$ is then achieved through a simultaneous fit to all the $\mathbb{E}(\phi(A_u))$ values across the toys and the different chosen thresholds u .

7.7.4.1 Generation of the background-only toys

A total of $N_{\text{toys}} = 20$ toy datasets were generated. For each background Monte Carlo (MC) sample b , the number of expected events at the preselection level, denoted as n_b , is calculated. The toy generation procedure involves combining random MC events drawn from each background sample b , such that the number of events follows a Poisson distribution centered at n_b . However, additional complexity is introduced to account for the presence of negative MC weights.

Before drawing the MC events, each background sample is divided into two subsamples, labeled as Sample $(b,+)$ and Sample $(b,-)$, containing events with positive and negative MC weights, respectively. Two positive quantities, n_b^+ and n_b^- , are defined to satisfy the following conditions:

$$\begin{cases} n_b^+ - n_b^- = n_b \\ n_b^- = f_b \cdot (n_b^+ + n_b^-) \end{cases} \quad (7.9)$$

Here, f_b represents the fraction of negatively weighted MC events in the background sample b at the preselection level. Two independent Poisson distributions, centered at n_b^+ and n_b^- , denoted as $\text{Pois}(x|n_b^+)$ and $\text{Pois}(x|n_b^-)$, are used to extract N_{toys} integers $x_i^{b,+}$ and $x_i^{b,-}$ for $i = 1, \dots, N_{\text{toys}}$. In other words, MC events are drawn from the two subsamples Sample ($b, +$) and Sample ($b, -$) using the following:

$$\begin{cases} x_i^{b,+} \sim \text{Pois}(x|n_b^+) \\ x_i^{b,-} \sim \text{Pois}(x|n_b^-) \end{cases} \quad (7.10)$$

For the generation of the i^{th} toy dataset, $x_i^{b,+(-)}$ MC events are randomly sampled from the subsample Sample($b, +(-)$), with each event assigned a weight of +1 (-1) when constructing the distributions of any physical observable (e.g., $m_{\gamma\gamma}$ or the PNN output, which serves as the final discriminant in the fit). The selection of $x_i^{b,+(-)}$ events is random, and to account for the meaning of MC weights, each event is drawn with a probability proportional to its MC weight (which includes pileup corrections and scale factors), normalized to unity.

A $\gamma\gamma$ K-factor is applied to adjust the overall normalization of the non-resonant background processes (including $\gamma\gamma + \text{jets}$, $t\bar{t}\gamma\gamma$, and $Z \rightarrow b\bar{b}(q\bar{q}) + \gamma\gamma$) to match the data.

- A K-factor $K_1(\gamma\gamma) = 1.03$ is applied to $\gamma\gamma + \text{jets}$ events that pass the 1 b -tagged selection.
- A K-factor $K_2(\gamma\gamma) = 1.27$ is applied to $\gamma\gamma + \text{jets}$ events that pass the 2 b -tagged selection.

These additional K-factors are included when selecting $\gamma\gamma + \text{jets}$ events for the toy generation. A total of $N_{\text{toys}} = 20$ background-only toys were created by combining events from the different background (sub-)samples b . The distributions of $m_{\gamma\gamma}$ for the background-only MC samples, for each toy, and for data in the sidebands are shown in Figure 7.33, considering the events that meet the common preselection, as well as those in the 1 b -tagged and 2 b -tagged categories, respectively.

7.7.4.2 Performing the $SH \rightarrow b\bar{b}\gamma\gamma$ analysis on each toy

The full $SH \rightarrow b\bar{b}\gamma\gamma$ analysis is carried out for each toy, and the test statistic is calculated at each (m_X, m_S) point within the 2D search space. The discovery test statistic q_0 [225] is employed:

$$q_0 = \begin{cases} -2 \ln(\Lambda(0)) & \text{if } \hat{\mu} > 0 \\ 0 & \text{if } \hat{\mu} \leq 0 \end{cases} \quad (7.11)$$

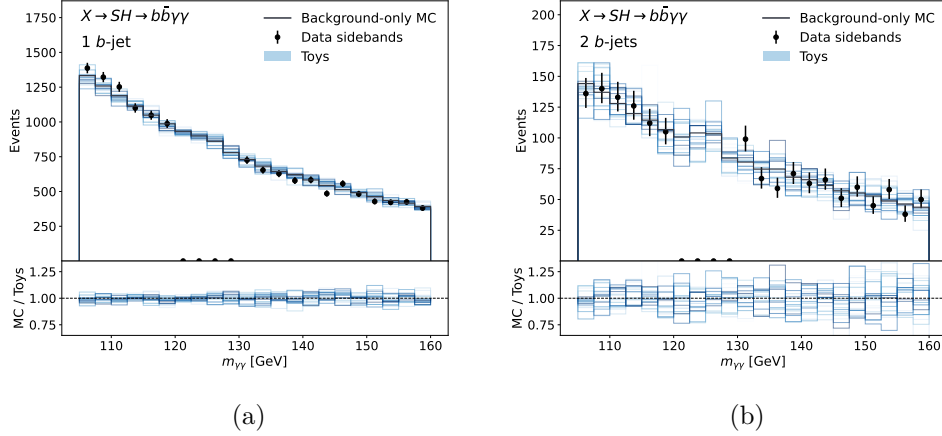


Fig. 7.33: Comparison of the $m_{\gamma\gamma}$ distributions for the total background MC sample (solid black line, including all non-resonant backgrounds, single Higgs backgrounds, and non-resonant HH backgrounds), the data sidebands (black markers), and $N_{\text{toys}} = 20$ toy experiments (faint blue lines) after the common preselection in the 1 b -tagged category (a) and the 2 b -tagged category (b). In both regions, the toy distributions fluctuate around the background MC sample (used as the basis for toy generation), and their normalization is correctly matched to the data in the sidebands.

where $\Lambda(0)$ is the profile likelihood ratio, defined as $\Lambda(0) = \frac{\mathcal{L}(0, \hat{\theta}(0))}{\mathcal{L}(\hat{\mu}, \hat{\theta})}$. Here, $\hat{\mu}$ and $\hat{\theta}$ represent the best-fit values for the signal strength and nuisance parameters in the unconditional fit, while $\hat{\theta}(0)$ is the conditional best-fit for the nuisance parameters when the signal strength is fixed to zero.

For each i^{th} toy, a 2D map of the test statistic q_0 can be generated (which can later be used for calculating the Euler characteristic at chosen thresholds u). As an illustration, the 2D map of $q_0 = q_0(m_X, m_S)$ is shown in Figure 7.34 for toy number 0.

7.7.4.3 Evaluation of the Euler characteristics and the global p_0

The 2D maps of the test statistic q_0 for each toy are utilized to compute the Euler characteristic $\phi(A_u)$ for four thresholds: $u = 1.0, 2.0, 4.0$, and 6.0 . A simultaneous fit to the Euler characteristic distributions $\phi(A_u)$ from each toy, across all thresholds, is performed to extract $\mathcal{N}1$ and $\mathcal{N}2$. Specifically, for a given threshold u_1 , the Euler characteristic $\phi(A_{u_1})$ for each toy is modeled by a Poisson distribution with mean λ_1 . The Poisson means are not independent but follow Equation 7.8:

$$\lambda(u) = \mathbb{P}(\chi^2 > u) + e^{-u/2} \cdot (\mathcal{N}1 + \sqrt{u} \cdot \mathcal{N}2) \quad (7.12)$$

This simultaneous fit extracts the values of $\mathcal{N}1$ and $\mathcal{N}2$, including their uncertainties, which account for limited toy statistics and correlations among the Euler

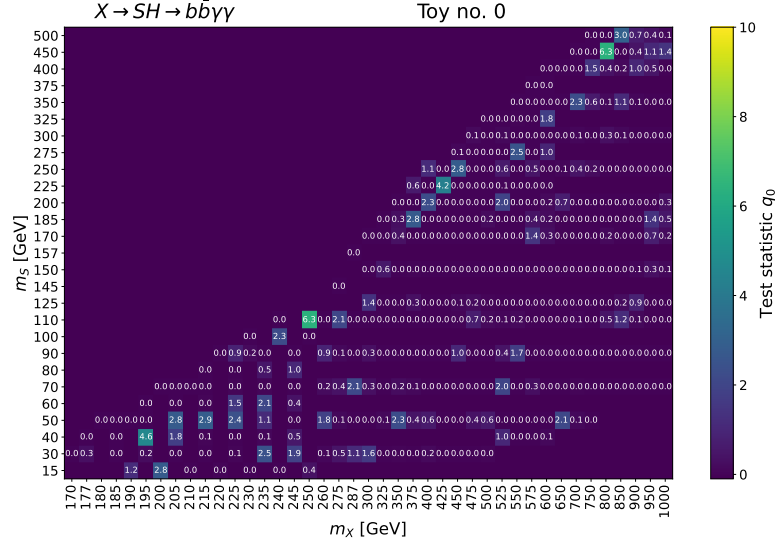


Fig. 7.34: A 2-dimensional map of the test statistic q_0 as a function of the (m_X, m_S) signals for the background-only toy experiment no. 0.

characteristics at different thresholds. The fit is performed under the constraint that $\mathcal{N}2$ is non-negative. The fitted values are:

- $\mathcal{N}1 = 25.067 \pm 1.100$
- $\mathcal{N}2 = 0.000 \pm 8.33 \times 10^{-12}$

The fitted curve of the Euler characteristic as a function of q_0 can then be converted into a curve representing the global significance as a function of the maximum local significance. Given the test statistic q_0 , the p-value is calculated as [225]:

$$p_0 = \int_{q_0}^{+\infty} f(x|0), dx \quad (7.13)$$

where:

$$f(x|0) = \frac{1}{2}\delta(x) + \frac{1}{2} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{2}} e^{-x/2} \quad (7.14)$$

The p_0 values can be converted into significance values Z_0 via:

$$\int_{Z_0}^{+\infty} \text{Gauss}(x|0, 1), dx = \frac{p_0}{2} \quad (7.15)$$

where $\text{Gauss}(x|0, 1)$ represents a Gaussian distribution centered at zero with unit standard deviation. For the $SH \rightarrow b\bar{b}\gamma\gamma$ analysis, the maximum local significance is 3.55σ , corresponding to a global significance of $1.992 \pm (-0.016, +0.021)$. The local and global p_0 values, along with the trial factor (the ratio of local to global p_0), are summarized in Table 7.24.

Table. 7.24: The maximum values of the local p_0 , global p_0 , and the corresponding trial factor.

Maximum of the local p_0	0.000385
Global p_0	0.046358
Trial factor (global p_0 / local p_0)	240.678

7.8 Conclusion

The search is performed for a signal from a hypothetical scalar particle X , which is considered to decay into another hypothetical scalar S and a Higgs boson, with subsequent decays into pairs of b -quarks and photons, respectively. The analysis targets two signal regions focusing on resolved or boosted $S \rightarrow b\bar{b}$ decays, employing the parameterised neural network (PNN) that provide continuous sensitivity across the probed (m_X, m_S) plane. For the mass region where $m_X > 300$ GeV and $m_S > 70$ GeV, the limits for intermediate mass points are validated by interpolating the signal shapes onto a finer grid, which is guided by the PNN's sensitivity range for values of (m_X, m_S) where it is not directly trained. At lower masses, the validation of the limits for intermediate mass points is ensured by using a very fine grid of simulated signal samples.

No significant excess relative to the Standard Model background is observed. Consequently, 95% confidence level (CL) upper limits are set on the cross-section $\sigma(X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma)$ within the ranges $170 \leq m_X \leq 1000$ GeV and $15 \leq m_S \leq 500$ GeV, extending earlier LHC results to lower masses and improving sensitivity. The most significant deviation from the background-only expectation is observed for $(m_X, m_S) = (575, 200)$ GeV, with a local (global) significance of 3.5 (2.0) standard deviations. For the mass point $(m_X, m_S) = (650, 90)$ GeV, where CMS reported an excess with a local (global) significance of 3.8 (below 2.8) standard deviations, this analysis shows good agreement with the background-only hypothesis, setting a 95% CL upper limit on the signal cross-section at 0.2 fb.

CHAPTER 8

Conclusion and Prospects

In this thesis, two key analyses based on ATLAS Run 2 data have been presented: the electroweak production of $W\gamma jj$ via vector boson scattering (VBS) and the search for a hypothetical decay $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$. Both studies contribute substantially to expanding our understanding of the Standard Model (SM) and probing potential new physics scenarios.

8.1 Summary of Results

The electroweak production of $W\gamma jj$ is observed for the first time by the ATLAS collaboration. This process provides a unique test of quartic gauge couplings via vector boson scattering, specifically probing $WW\gamma Z$ and $WW\gamma\gamma$ interactions. The fiducial cross-section for electroweak $W\gamma jj$ production is measured as 13.2 ± 2.5 fb, consistent with theoretical predictions from MadGraph5+Pythia8 and Sherpa. Advanced machine learning techniques, such as neural networks, are employed to enhance signal-background separation, and differential cross-sections are measured using kinematic observables. These results are also interpreted within the framework of effective field theory, setting the first LHC constraints on the dimension-8 operators f_{T3} and f_{T4} , providing key insights for future theoretical developments.

The second analysis focuses on the search for a higgs like scalar particle X decaying into a lighter scalar S and a Higgs boson, with subsequent decays into $b\bar{b}$ and $\gamma\gamma$. The search utilizes parameterised neural networks to provide continuous sensitivity across the m_X - m_S plane. No significant excess is observed over the Standard Model background, leading to the establishment of 95% confidence level upper limits on the cross-section for $X \rightarrow S(\rightarrow b\bar{b})H(\rightarrow \gamma\gamma)$, covering the X mass range from 170 GeV to 1000 GeV and S masses between 15 GeV and 500 GeV. The most significant deviation is found at $(m_X, m_S) = (575, 200)$ GeV with a local (global) significance of 3.5 (2.0) standard deviations. For the mass point $(m_X, m_S) = (650, 90)$ GeV, where CMS reported an excess with a local (global)

significance of 3.8 (below 2.8) standard deviations, this analysis shows good agreement with the background-only hypothesis, setting a 95% CL upper limit on the signal cross-section at 0.2 fb.

8.2 Prospects

With the beginning of ATLAS Run 3, the integrated luminosity is expected to exceed 300 fb^{-1} as shown in Figure 8.1, effectively doubling the available data from Run 2. This expanded dataset will significantly enhance the statistical power of both the $W\gamma jj$ and $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ analyses.

The inclusive $W\gamma$ analysis aims to investigate events containing a photon and a W boson decaying leptonically, exploring both electroweak and QCD contributions. The main physics goals of this analysis include measuring the differential cross-sections across various observables, such as the transverse momenta of the photon and lepton, as well as the invariant mass of the lepton-photon system. Additionally, the analysis seeks to probe potential CP-violating effects and test the predictions of the Standard Model through effective field theory (EFT) operators, such as $O_{\phi\tilde{W}B}$ and $O_{\tilde{W}}$. The radiation amplitude zero (RAZ) effect is also explored as part of this study. By performing a detailed examination of these observables, the inclusive $W\gamma$ analysis provides valuable input for understanding the underlying production mechanisms and their consistency with Standard Model predictions, paving the way for further studies on more specific processes, such as vector boson scattering and new physics searches.

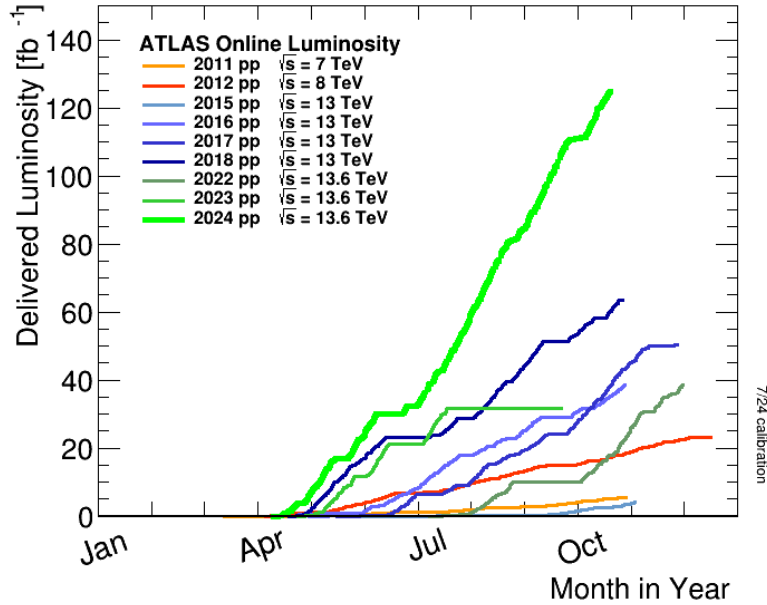


Fig. 8.1: The cumulative luminosity as a function of day, delivered to ATLAS during periods of stable beams and high-energy proton-proton collisions.

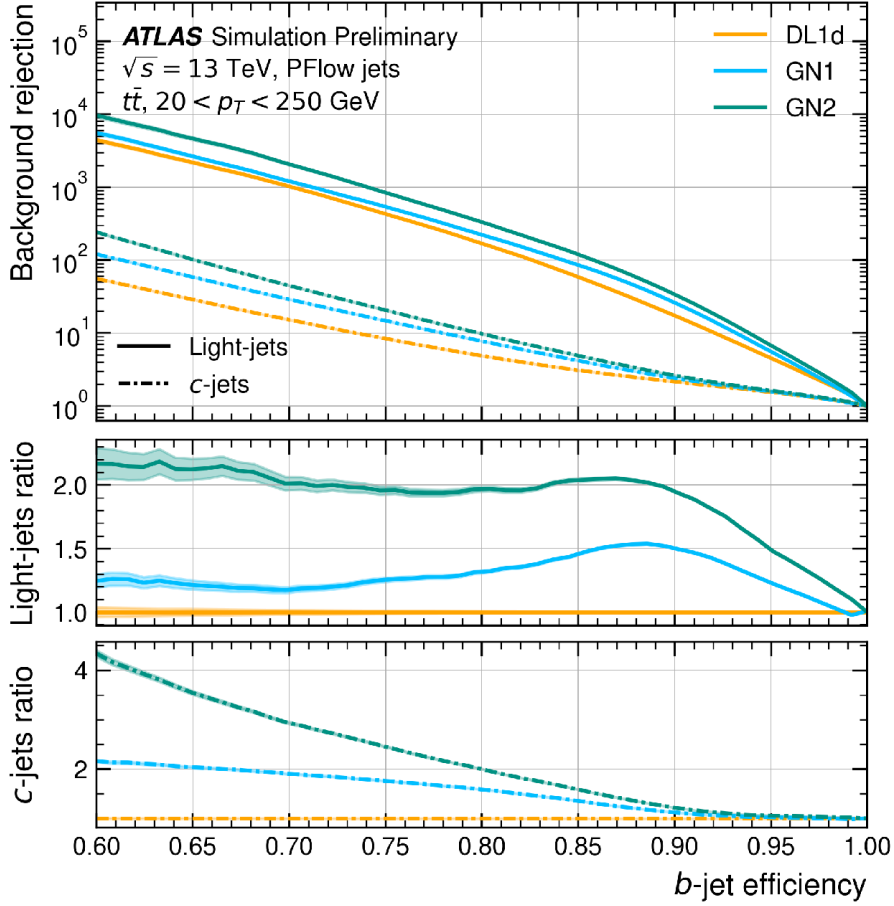


Fig. 8.2: The rejection rates for c -jets and light-flavor jets are presented as a function of the b -jet tagging efficiency for jets in a Z' sample with $250 < p_T < 6000$ GeV. The bottom panels display the ratio of these rejections relative to the performance of the DL1d algorithm. DL1d is a variant of the DL1r tagger [26], where the RNNIP network is replaced by the DIPS network [27]. GN2, an upgraded version of the GN1 tagger [28], benefits from a refined training process and an optimized transformer architecture. In the calculation of the tagging discriminant, $f_c = 0.018$ is used for DL1d, $f_c = 0.05$ for GN1, and $f_c = 0.1$ for GN2. The shaded regions represent binomial statistical uncertainty bands. All taggers were tested using the ATLAS software framework.

The full Run 2 + partial Run 3 analysis of $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ is likely to use the same event selection criteria, signal region definitions, and parameterised neural network (PNN) algorithms as those employed in the full Run 2 analysis. The GN2 [227] tagger will be used, which represents an improvement over the previous DL1r tagger. GN2 leverages a graph neural network architecture and transformer-based techniques to enhance the identification of b -quark jets across various mass regimes. With more data and an improved b -tagging algorithm, there is potential for an increase in sensitivity.

Moving forward, the full Run 3 analysis will employ GN2X [228], an extended version of GN2 designed to handle boosted $S \rightarrow b\bar{b}$ decays more effectively. GN2X

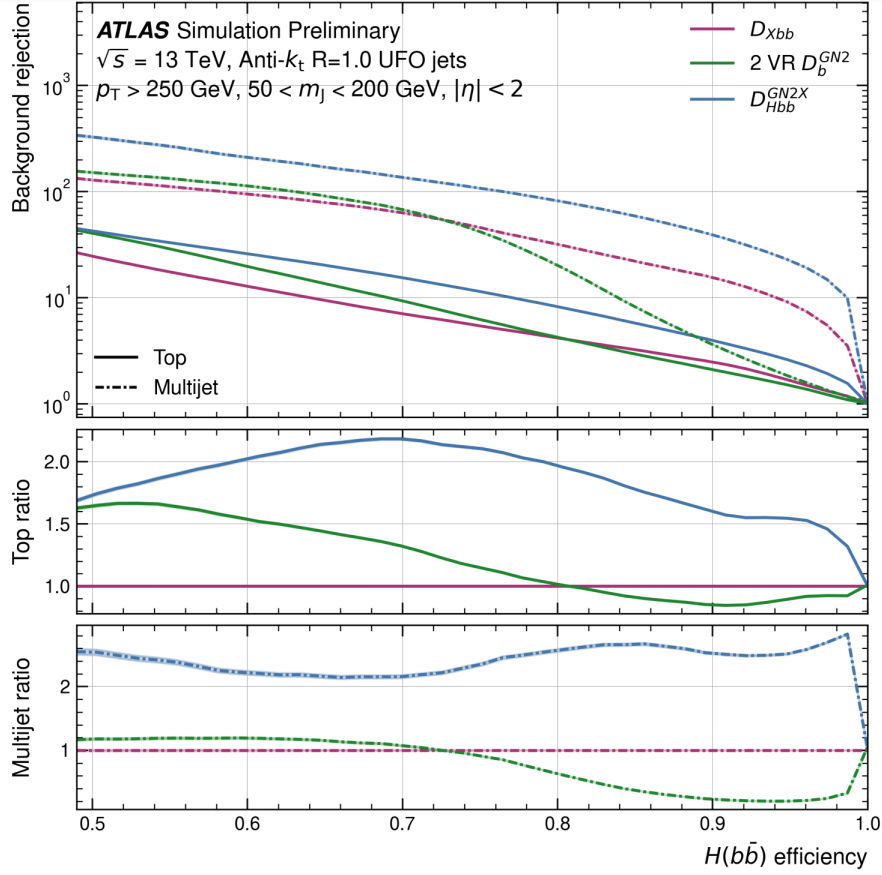


Fig. 8.3: Top and multijet rejection rates are shown as a function of the $H(b\bar{b})$ tagging efficiency for jets with $p_T > 250$ GeV and a mass in the range of $50 \text{ GeV} < m_J < 200 \text{ GeV}$. The performance of the GN2X algorithm is compared to the baseline algorithms D_{Xbb} and VR subjects. Statistical uncertainty bands, calculated using a binomial model, are indicated by the shaded regions. The distribution is based on Standard Model (SM) evaluation samples.

reconstructs these decays as large-radius jets and utilizes advanced jet kinematics and photon-large- R jet ΔR selections to improve signal-to-background separation. Preliminary studies with GN2X indicate potential for better separation, especially in boosted scenarios. Additionally, the Run 3 analysis will investigate the effect of lowering the jet and photon p_T thresholds, which could provide further sensitivity improvements, though initial tests suggest only marginal gains. These adjustments, particularly the deployment of GN2X and lowered p_T thresholds, may help address the challenges posed by boosted decays in the full Run 3 analysis, potentially increasing the sensitivity of the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ search.

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Appendices

附录 A

Observation and differential cross-section measurements of electroweak $W \rightarrow (l\nu)\gamma jj$

A.1 NN performance

The training and validation loss of the neural network trained on even event number MC events and that trained on odd number MC events are shown in Figure A.2.

A.2 Expected Results

The event yields in both the control and signal regions, following the fit to the Asimov dataset, are presented in Figure A.1.

Table. A.1: The yields after the fit to the Asimov dataset in the signal region and the fit to the data in the control region.

	Signal Region	Control Region
EWK $W\gamma jj$	514.84 ± 83.46	121.44 ± 28.11
EWK $Z\gamma jj$	11.64 ± 1.00	6.61 ± 0.76
QCD $W\gamma jj$	1628.76 ± 111.42	1974.24 ± 137.97
Top Bkg.	110.32 ± 18.52	188.22 ± 38.02
QCD $Z\gamma jj$	115.39 ± 33.77	144.43 ± 68.88
$j \rightarrow \gamma$	402.40 ± 47.02	408.42 ± 56.11
$e \rightarrow \gamma$	147.78 ± 5.59	172.19 ± 6.12
$j \rightarrow l$	115.57 ± 16.06	113.27 ± 9.85
pileup γ	0 ± 0	11.18 ± 0.16
Total	3046.71 ± 63.86	3140 ± 95.27
Data	X	3143

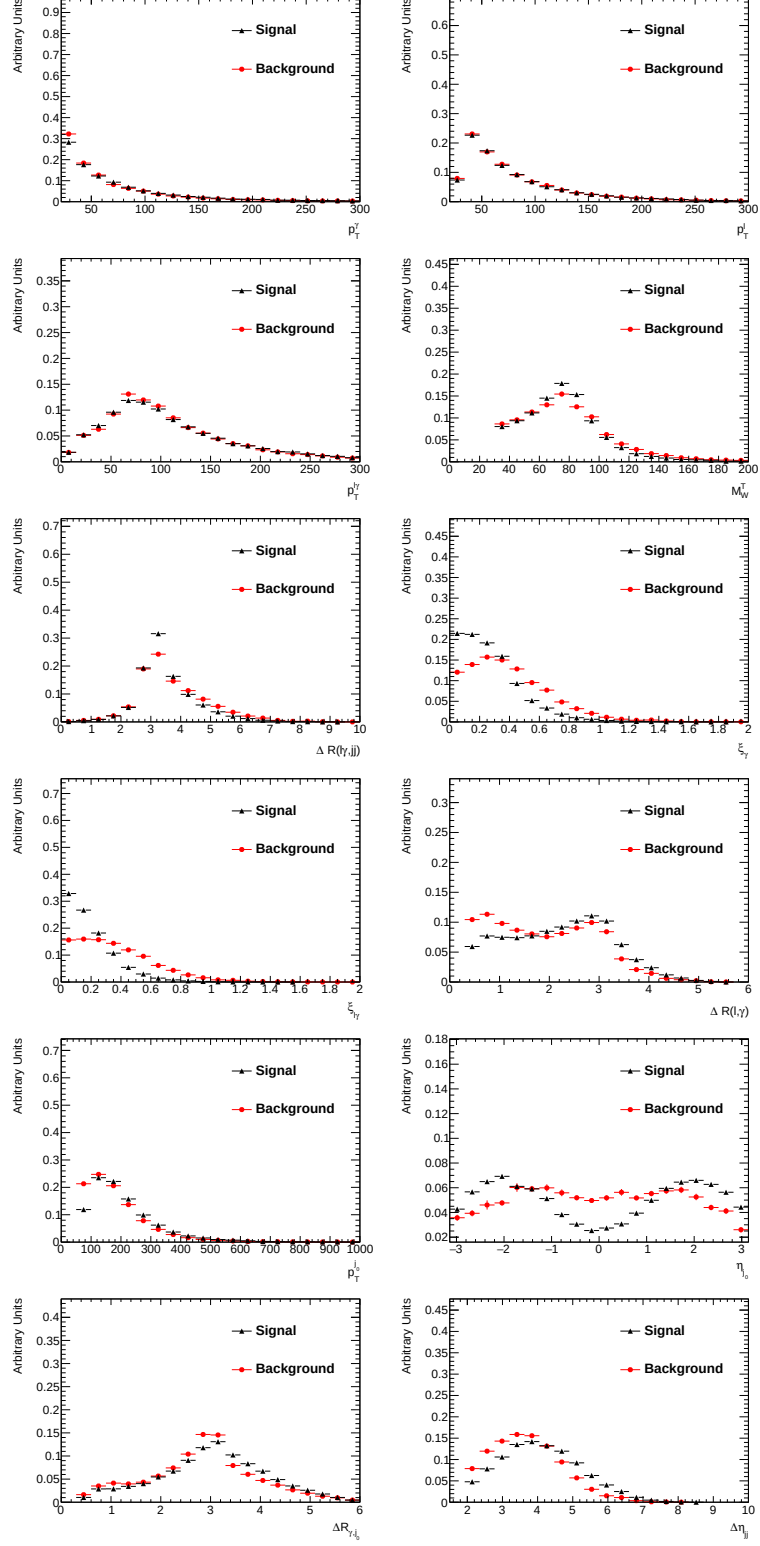


Fig. A.1: Comparison of the training variables for signal and background samples. All distributions have been normalized to one, allowing for a direct comparison of the shapes and behaviors of the variables between the signal and background datasets.

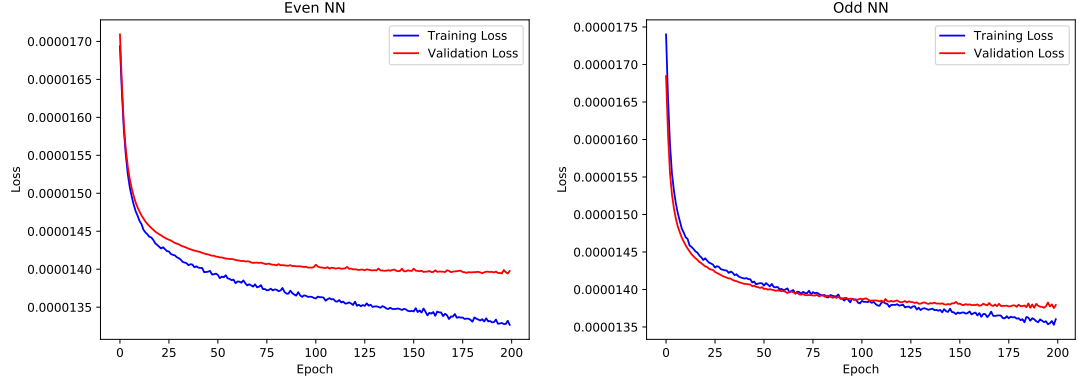


Fig. A.2: The loss curves are shown for the neural network trained on even event number MC (left) and odd event number MC (right).

Figure A.3 shows the pulls and constraints on the nuisance parameters related to the systematic uncertainties.

Figure A.4 presents the relative impact of the systematic and theoretical uncertainties on the parameter of interest.

Figure A.5 presents the negative log-likelihood profile as a function of the electroweak signal strength. The test statistic value at $\mu = 0$ is used to determine the expected significance.

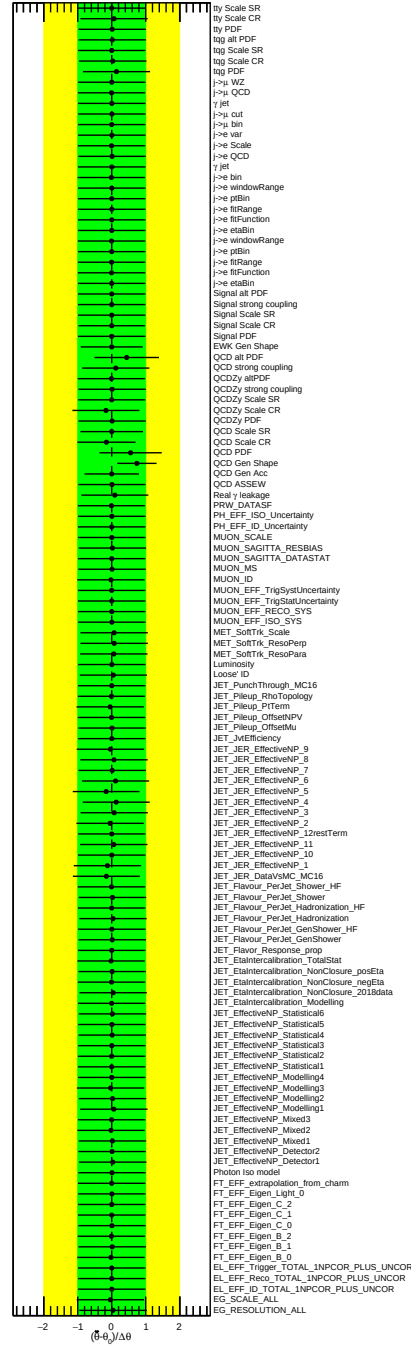


Fig. A.3: , illustrating how each parameter affects the overall fit quality.

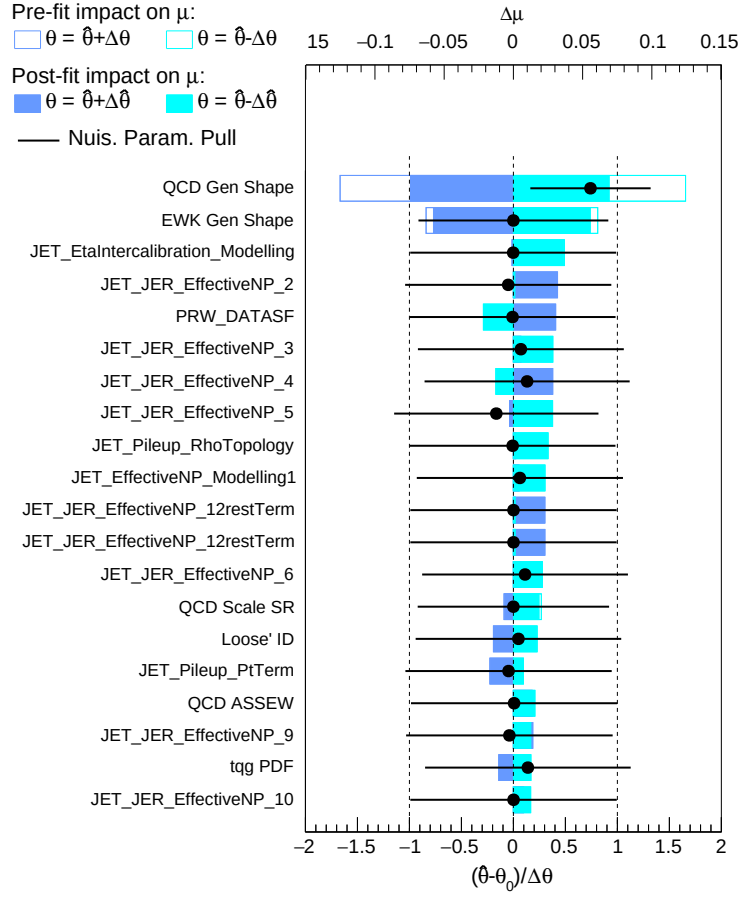


Fig. A.4: The effect of individual nuisance parameters on the parameter of interest (POI) is assessed, showing how each systematic uncertainty influences the measurement of the POI.

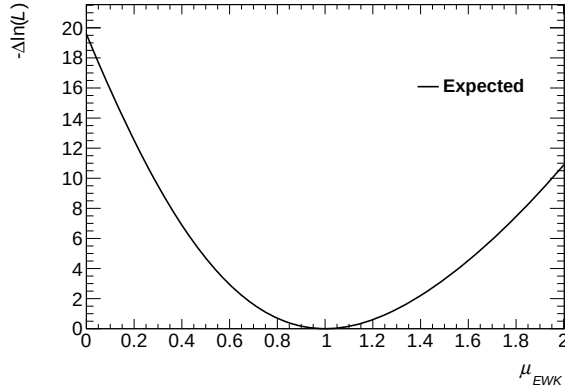


Fig. A.5: The likelihood scan for the parameter of interest (POI) is presented, comparing the results of fits performed with and without systematic uncertainties included.

A.3 Extraction of Fiducial Cross Section

A.3.0.1 Fiducial Volume Definition

- The event must include at least one prompt photon (classified as prompt via `MCTruthClassifier::isPrompt`) with $p_T > 22$ GeV and $|\eta| < 2.5$. The crack region between the barrel and endcap, $1.37 < |\eta| < 1.52$, is excluded. Photon isolation energy must satisfy $E_{\text{iso}} < 0.2 \times p_T^\gamma$. At truth level, isolation is determined by summing the transverse momentum of stable particles in a cone of $R = 0.4$ around the truth photon, excluding neutrinos.
- The event must contain one prompt electron or muon (again defined using `MCTruthClassifier::isPrompt`) with $p_T > 30$ GeV and $|\eta| < 2.5$. Leptons originating from tau decays are vetoed. Dressed lepton p_T is used. For electrons, the crack region between the barrel and the endcap ($1.37 < |\eta| < 1.52$) is excluded. Additionally, the invariant mass of the lepton-photon system must be within 10 GeV of the Z boson mass, consistent with the reconstructed-level selection.
- The event must include at least two jets with $p_T > 50$ GeV and $|\eta| < 4.4$. The jets are identified using the `AntiKt4TruthDressedWZJets` container, with jets defined as clusters of stable particles excluding prompt leptons, prompt neutrinos, and photons dressed to prompt leptons, as outlined in Ref. [229].
- The event's missing transverse energy (E_T^{miss}) must exceed 30 GeV. At truth level, E_T^{miss} is calculated using the transverse momenta of all non-interacting objects in the truth container.
- The event must satisfy $M_W^T > 30$ GeV, where M_W^T is calculated using the transverse momentum of the truth lepton and the truth E_T^{miss} .
- The angular separation criteria include: $\Delta\Phi(j_{1(2)}, E_T^{\text{miss}}) > 0.4$, $\Delta R(j_0, j_1) > 0.4$, $\Delta R(j_{0,1}, \gamma) > 0.4$, $\Delta R(j_{0,1}, l) > 0.4$, and $\Delta R(\gamma, l) > 0.4$.
- The event must contain no b-jets. The number of b-jets is determined using the `GhostBHadronsFinalCount` decoration.
- The dijet system must satisfy $M_{jj} > 500$ GeV and $\Delta Y(j, j) > 2$.

A.3.0.2 Choice of Photon Isolation Cut

At truth level, a photon isolation cut is applied to prevent extrapolation into regions of phase space with higher jet multiplicity, as events with a higher number of jets are more likely to fail the isolation requirement. However, applying

a stringent isolation cut at the truth level introduces sensitivity to the modelling of real emissions.

To mitigate this, the truth isolation cut is determined by performing a linear fit between the reconstructed isolation profile and the corresponding truth isolation value. This approach ensures that the truth isolation cut aligns with the reconstructed isolation threshold. Only reconstructed photons that are matched to a truth photon are included in the fit, and to minimize resolution-induced biases, the truth photon E_T threshold is set below the reconstructed photon E_T threshold. Given the resolution effects, 50% of events at the truth isolation cut value are expected to pass the reconstructed isolation criterion. This method reduces the dependence on the model, thus improving robustness. The relationship between truth and reconstructed isolation is illustrated in Figure A.6, from which a truth isolation cut of $E_{\text{iso}}^{\text{truth}} < 0.2 \times E_T^{\gamma, \text{truth}}$ is recommended.

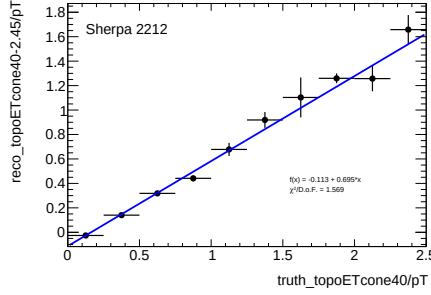


Fig. A.6: A comparison between truth photon isolation and reconstructed photon isolation is presented. The profile is fit, and the value of the fitted function at the isolation cut for reconstructed photons is used to determine the corresponding isolation cut for truth photons.

Figure A.7 displays the ratio of events that pass the reconstructed-level isolation requirement to those that fail, plotted as a function of truth photon isolation scaled by the truth photon transverse energy. At $E_{\text{iso}}^{\text{truth}}/E_T^{\gamma, \text{truth}} < 0.2$, approximately 50% of the events pass the reconstructed isolation criterion, while the other 50% fail. This confirms that the approach is functioning as intended, accurately mapping the truth-level isolation to the reconstructed isolation behavior.

To assess the potential bias introduced by using the Sherpa signal sample to determine the isolation cut, the same analysis is repeated using the MadGraph sample. The fit between truth and reconstructed isolation, along with the pass-to-fail ratio as a function of scaled truth isolation, is presented in Figure A.8. This comparison ensures consistency across different generators and validates that the isolation cut determination is not overly dependent on the specific signal generator used.

As seen in Figure A.8, the MadGraph sample also indicates an isolation cut of

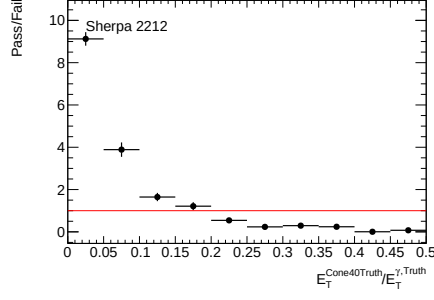


Fig. A.7: The ratio of events that pass the reconstructed-level isolation cut to those that fail is presented in bins of truth photon isolation, scaled by the truth photon transverse energy.

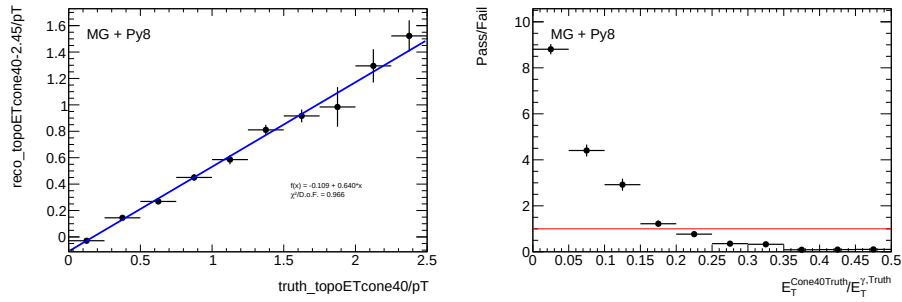


Fig. A.8: A comparison of truth photon isolation versus reconstructed photon isolation in MadGraph is presented, highlighting the relationship between the two variables. Additionally, the ratio of events that pass the reconstructed-level isolation cut to those that fail is shown in bins of scaled truth photon isolation, based on MadGraph simulations.

$E_{iso}^{truth} < 0.2E_{\gamma,truth}^T$. This consistency between the MadGraph and Sherpa samples further supports the robustness of the chosen isolation cut and minimizes concerns regarding generator dependence.

A.4 Asimov Results in Signal Extraction

Figure A.9 shows the total systematic uncertainties in different categories of experimental and theoretical sources with asimov dataset. Figure A.10 shows the extracted signal with total systematic and statistical sources.

A.4.0.1 Asimov Results in Unfolding

This section presents Asimov unfolded yields and differential unfolded distributions for EW components in the signal region. Total systematic uncertainties are estimated by calculating quadratic sum of statistical, experimental and theoretical uncertainties mentioned in above sections. A summary of all the systematic uncertainties discussed above in Figure A.11.

Figure A.12 shows the unfolded EW $W\gamma$ differential cross-section distribu-

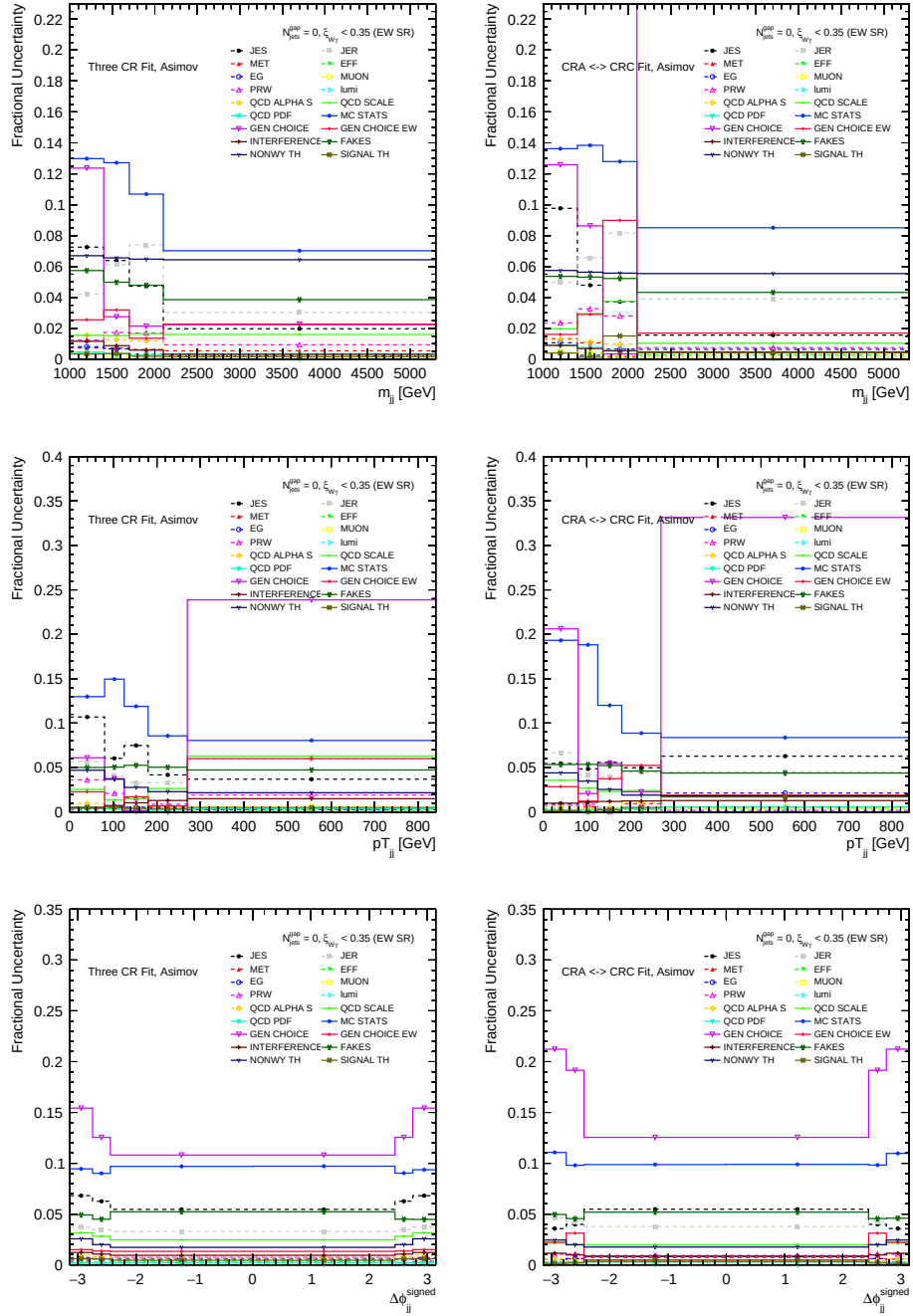


Fig. A.9: Systematic uncertainty values for the nominal CRA method and the CRC method after smoothing are presented for the central value of the extracted signal. The systematic uncertainties derived using the CRC method exhibit larger statistical fluctuations compared to the CRA method, as evidenced by the observed jumps in the generator choice uncertainty. This occurs because the CRC method is now primarily used to constrain the QCD background b_L , but the CRC region contains a relatively small number of *strong* $W\gamma jj$ events, leading to substantial fluctuations in b_L . In contrast, when the CRC method is primarily used to derive $f(x)$ (as in the nominal case), the requirement for a control region with a large event count is minimized since $f(x)$ is defined as a constant, and no shape extraction is needed for the residual correction.

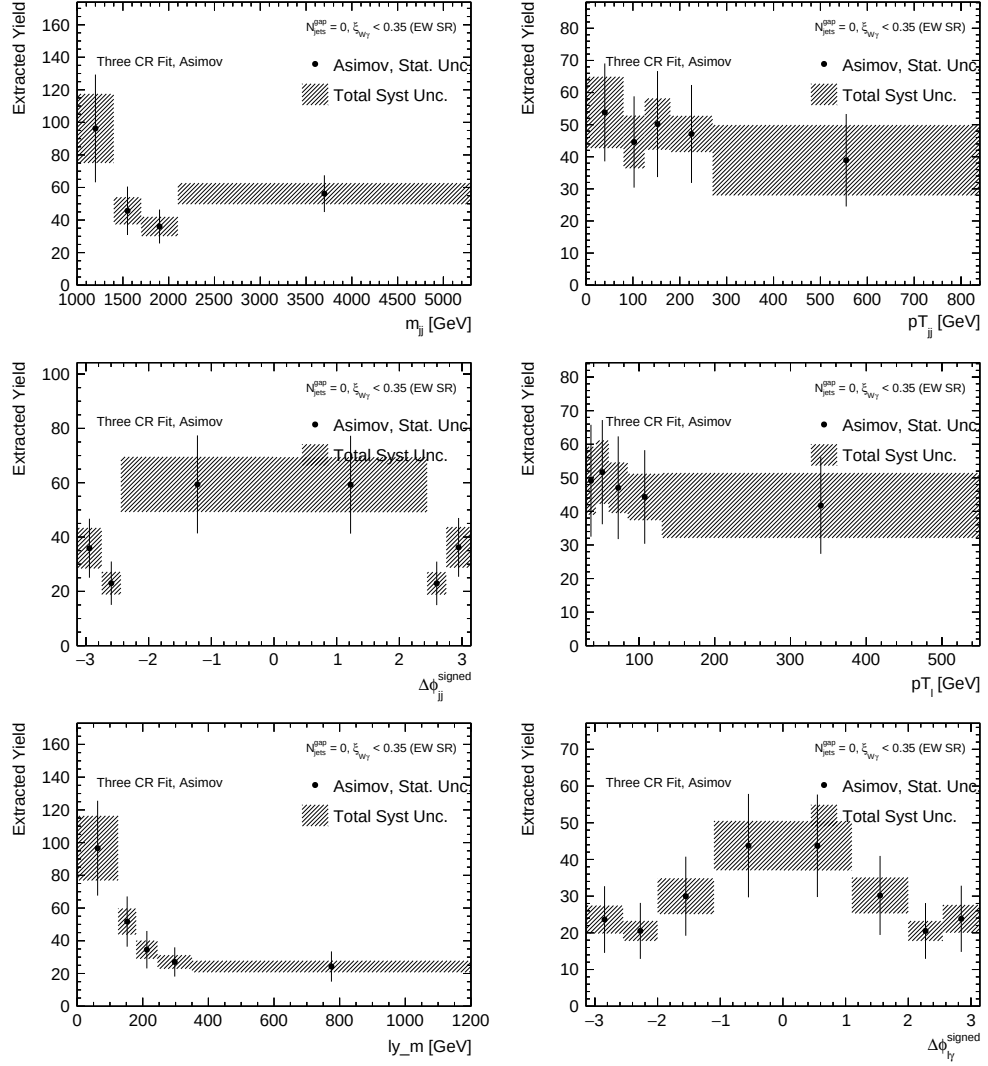


Fig. A.10: The final extracted $EW W\gamma jj$ yield in the signal region (SR), along with the associated statistical uncertainty from the Asimov dataset and systematic uncertainties after smoothing, is presented.

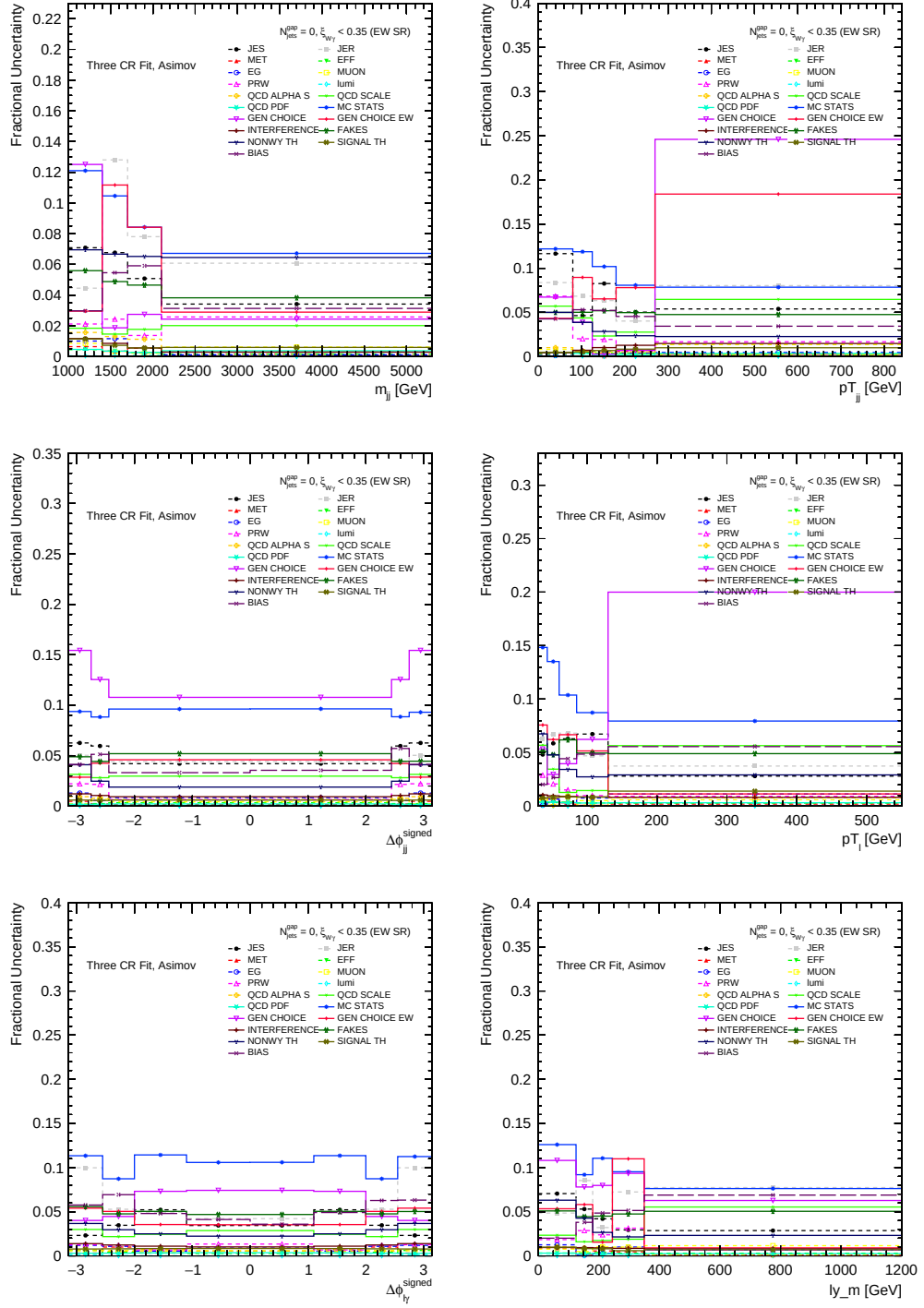


Fig. A.11: Systematic uncertainties for the 3CR fits, with all terms added in quadrature, are presented for the m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$ distributions. These uncertainties are shown for the combined electron and muon channels.

tions.

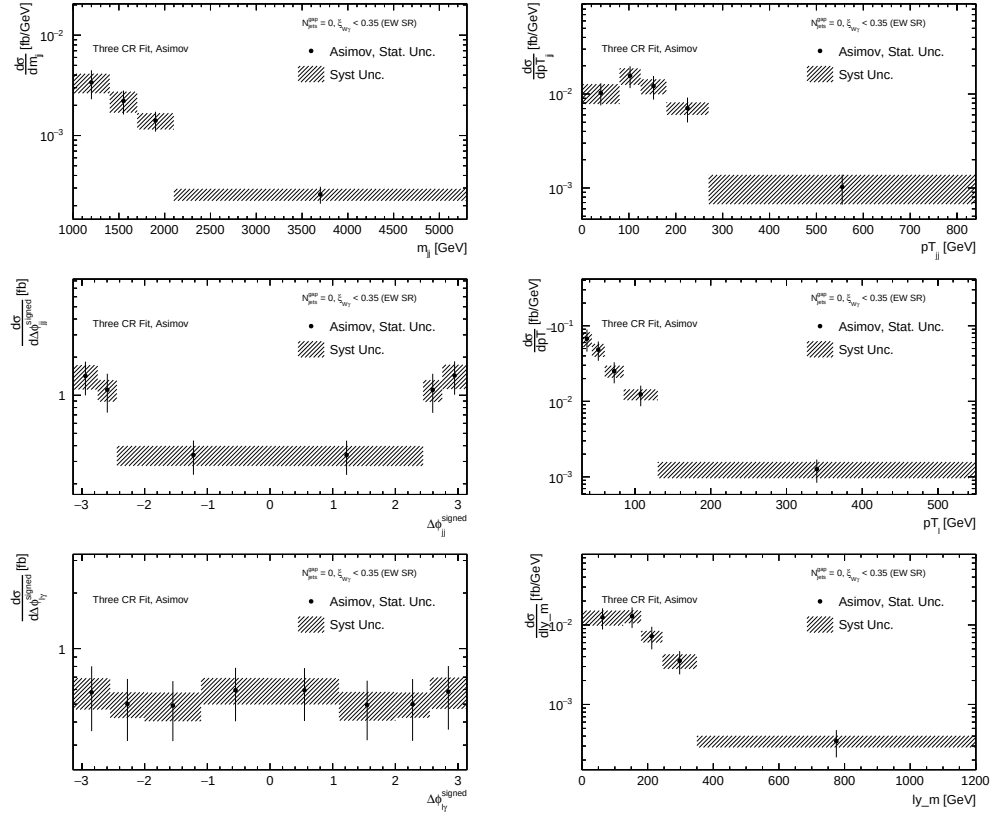


Fig. A.12: The unfolded electroweak (EW) $W\gamma$ differential cross-section distributions for m_{jj} , p_T^{jj} , $\Delta\phi_{jj}$, p_T^l , $m_{l\gamma}$, and $\Delta\phi_{l\gamma}$ are shown for the combined electron and muon channels. These distributions are obtained after applying signal region (SR) selections and the unfolding procedure.

附录 B

Search for a resonance decaying into a scalar particle and a Higgs boson in the final state with two bottom quarks and two photons

B.1 Interpolation

B.1.1 Signal interpolation

Monte Carlo (MC) simulations generate signal events at a discrete set of mass points within the (m_X, m_S) parameter space, as covering the entire mass range would be computationally prohibitive. To address this, signal events are produced at selected mass points, and the intermediate points are estimated through interpolation techniques. The objective is to reconstruct the distribution $p(m_{bb\gamma\gamma}, m_{bb} \mid m_X, m_S)$ for specific truth-level masses, by interpolating key observables such as $m_{bb\gamma\gamma}$ and m_{bb} . Predictive uncertainties are incorporated as systematic uncertainties in the statistical model to account for resolution degradation in regions without direct simulations. Two interpolation techniques, Lorentz transformation and normalizing flow, were explored, with the Lorentz transformation chosen for its computational efficiency.

B.1.1.1 Lorentz Transformation

The kinematic properties of two-body decays can be analytically derived from the masses of the parent particle and its two daughter particles, provided these are considered in the rest frame of the parent particle. Specifically, for the decay process $X \rightarrow SH$, the energy and momentum of particle S in the rest frame of X are given by:

$$|\vec{p}_S^X|(m_X, m_S) = |\vec{p}_H^X| = \sqrt{\frac{[(m_X^2 - (m_H + m_S)^2)(m_X^2 - (m_H - m_S)^2)]}{2m_X}}, \quad (\text{B.1})$$

where the superscript X indicates the rest frame of X .

Using this relation, S_{reco} can be reconstructed from the di- b quark system, H_{reco} from the di-photon system, and subsequently X_{reco} from S_{reco} and H_{reco} . The Lorentz vector of X_{reco} is employed to determine the necessary Lorentz boost to transform into the rest frame of X_{reco} . This Lorentz boost is then applied to the Lorentz vectors of both S_{reco} and H_{reco} . Utilizing Equation B.1, a momentum scaling factor is calculated as follows:

$$R_p = \frac{|\vec{p}_S^X|(m_X^{\text{target}}, m_S^{\text{target}})}{|\vec{p}_S^X|(m_X^{\text{init}}, m_S^{\text{init}})}. \quad (\text{B.2})$$

The assumption here is that this linear transformation can be used to map one mass point to another. This scaling factor is then applied to the momentum vectors of S_{reco} and h_{reco} in the rest frame. Additionally, the mass of S_{reco} is scaled by the ratio $\frac{m_S^{\text{target}}}{m_S^{\text{init}}}$.

While transforming the momentum scale to the target mass point tuple $(m_X^{\text{target}}, m_S^{\text{target}})$ via the Lorentz transformation, the momentum resolution remains unaffected. Figure B.1 illustrates the mass resolution $\Delta M = \frac{m_{bb} - m_S}{m_S}$ across different m_X and m_S . Significant variation in resolution with respect to m_X and m_S necessitates careful handling during interpolation.

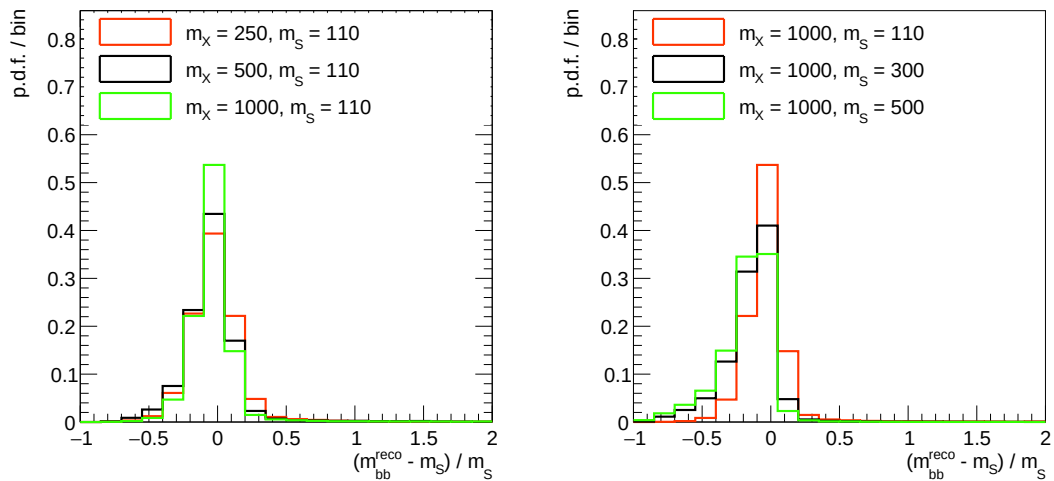


Fig. B.1: Mass resolution $\Delta M = \frac{m_{bb} - m_S}{m_S}$ is shown on the left for a fixed m_S and on the right for a fixed m_X .

To address this, the mass resolution is adapted to the target mass resolution

using an event-based weight w_{res} when populating the histograms. The event weight w_{res} is defined as:

$$w_{\text{res}} = \frac{\text{probability density of } \Delta M^{\text{target}}}{\text{probability density of } \Delta M^{\text{init}}}(\Delta M^{\text{target}}). \quad (\text{B.3})$$

Given the mass resolution of the initial mass point tuple is known, the target mass resolution must be interpolated. This involves performing a binned maximum likelihood fit with a parameterised form for all generated signal MC mass points using RooFit [230]. The Bukin probability density [231] is utilized to parameterize the ΔM probability density. The five parameters of the Bukin probability density are stored in a grid as functions of m_S and m_X . From this grid, each parameter is interpolated to the target mass point tuple $(m_X^{\text{target}}, m_S^{\text{target}})$ using Delaunay triangulation [232]. These interpolated parameters are then used to construct the Bukin probability density, allowing for the calculation of w_{res} on an event-by-event basis. Figure B.2 depicts the fit result for the mass resolution on the left and the interpolation result on the right for the sample point $m_X^{\text{target}} = 750$ GeV and $m_S^{\text{target}} = 200$ GeV. The MC predicted mass resolution agrees well with the interpolated prediction. Figure B.3 shows the interpolation results of the mass distributions and the PNN score for the same mass point. All interpolated signals are generated by applying the Lorentz transformation to a high-statistics MC signal: $m_X = 500, m_S = 170$.

This interpolation method does not cover the entire mass grid robustly. The expected discrepancies between limits derived from MC-generated or interpolated signals are used to determine the optimal mass grid for interpolation.

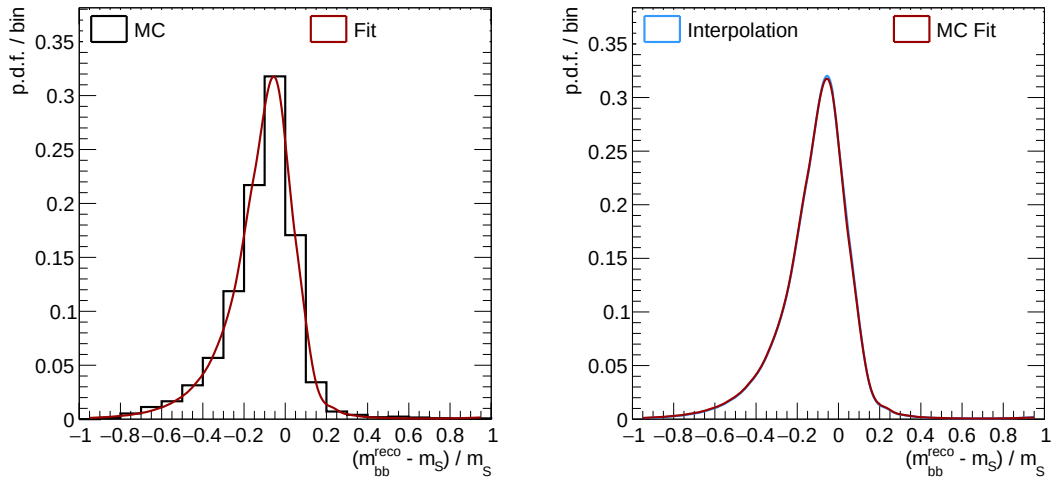


Fig. B.2: Mass resolution fit on the left, mass resolution interpolation on the right for the point $m_X^{\text{target}} = 750$ GeV and $m_S^{\text{target}} = 200$ GeV.

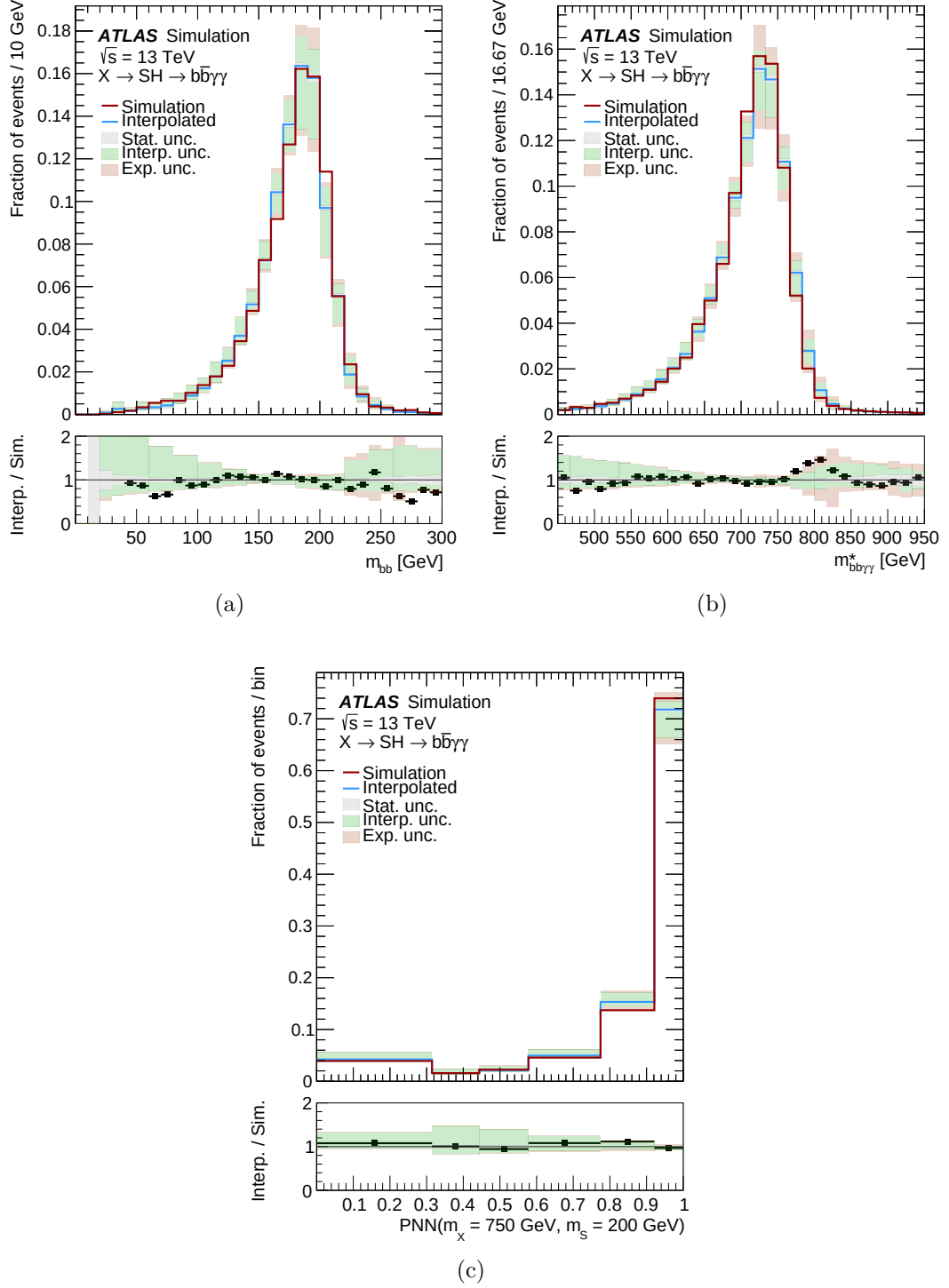


Fig. B.3: The comparison between the direct MC prediction and the interpolation is shown for (a) m_{bb} , (b) m_{bb}^* , and (c) the PNN score, with target values of $m_X = 750$ GeV and $m_S = 200$ GeV. The multi-colored band around the interpolated histogram represents the total uncertainty, which is derived as the quadratic sum of the statistical uncertainty, interpolation uncertainties of experimental data, and additional interpolation uncertainties discussed in Section B.1.2. Different colors in the band indicate the contribution of each uncertainty source. The lower portion of each figure displays the ratio of the interpolated results to the MC distributions.

B.1.1.2 Yield interpolation

Once the signal shape is appropriately interpolated using the method outlined in Section B.1.1.1, it must be accurately scaled before being used in the likelihood analysis. To accomplish this, a 2D interpolation method known as Delaunay triangulation [233] is employed to determine the absolute normalization of the interpolated signal for a signal with $\sigma \times \text{BR} = 1 \text{ fb}$.

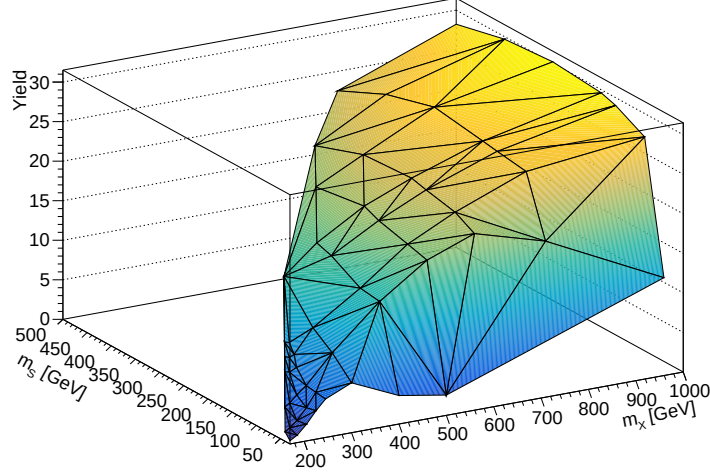


Fig. B.4: The 3D plot illustrates the yield at each point on the signal grid, evaluated in the 2 b -tagged category. The vertices correspond to the generated signal points with known yields from MC. The connecting lines and triangular surfaces between the vertices are created using Delaunay triangulation.

The yield distribution within the signal grid is represented on a 3D graph, with m_X on the x-axis, m_S on the y-axis, and the yield on the z-axis, as depicted in Figure B.4. The yield is calculated for the 2 b -tagged category. The vertices correspond to generated signal points with known yields from the MC. The connecting lines and triangular surfaces are generated through Delaunay triangulation. The yield for any arbitrary point in the m_X and m_S space is determined by the z-axis value of the intersection between a vertical line starting from that point and the surface of a triangle.

To evaluate the precision of yield interpolation using Delaunay triangulation, a signal point is removed from the grid and the triangulation is reconstructed. The interpolated yield is then calculated at the removed point and compared to the known yield from Monte Carlo (MC) simulations. The error estimates from this procedure are summarized in Table B.1.

Table B.1 shows the the error estimates from yield interpolation. Signal points with $m_X \leq 250 \text{ GeV}$ are excluded due to the dense clustering in this region, which facilitates interpolation with minimal uncertainty. Similarly, signals near

the merged region, probed by the 1 b -tagged category, are omitted as the steep drop in yield within the merged region affects the accuracy of yield predictions. The largest deviation, 5%, occurs at the point X750_S300, which is expected due to the larger interpolation distance required. This 5% discrepancy is conservatively adopted as the yield uncertainty for interpolated signals.

Table. B.1: List of signal points where yield interpolation uncertainty is assessed. The nominal yield refers to the value obtained directly from the signal MC simulation, while the interpolated yield is derived using Delaunay triangulation after excluding the corresponding point from the dataset.

m_X [GeV]	m_S [GeV]	Nominal yield	Interpolated yield	Relative difference [%]
300	70	8.75	8.44	-3.52
300	110	10.59	11.01	3.97
400	110	14.49	15.12	4.3
400	170	16.58	16.29	-1.73
400	200	17.19	16.98	-1.27
500	110	18.96	18.94	-0.11
500	170	19.93	20.15	1.13
500	200	20.75	19.90	-4.09
500	300	19.81	18.89	-4.64
600	110	21.90	21.40	-2.27
600	170	22.71	22.76	0.23
600	200	23.19	22.73	-1.98
600	300	22.81	22.76	-0.22
750	170	25.95	25.97	0.08
750	200	26.25	26.23	-0.06
750	300	27.17	25.84	-4.91
750	400	25.43	24.86	-2.26
1000	170	29.01	28.75	-0.89
1000	200	29.61	29.28	-1.11
1000	300	30.16	29.64	-1.73
1000	400	29.68	29.19	-1.65

By combining shape and yield interpolation, it is possible to model the distribution for any signal point within the bounds of the signal grid.

B.1.2 Systematic uncertainty

To analyze the systematic uncertainty inherent in the interpolation method, we examine the fit parameters of the Bukin probability density. For each of the five parameters, we adjust the mass resolution interpolation, as illustrated in Figure B.2, by varying each fit parameter upwards and downwards in accordance with the fit's uncertainty. For each variation in mass resolution interpolation, the interpolated PNN shape is recalculated. Given that multiple parameters of the Bukin function are correlated, the total variation envelope is considered as the

systematic uncertainty. To provide a comprehensive view of this uncertainty, Figure B.5 displays the uncertainty value (both upward and downward variations) in the final bin of the PNN score. Typically, the difference between the nominal and systematically shifted PNN shapes ranges from 5% to 20%, with the highest values observed near the $m_X = m_S + m_H$ boundary. Further details on the interpolation of experimental systematic uncertainties are presented in Section 7.6.7.1.

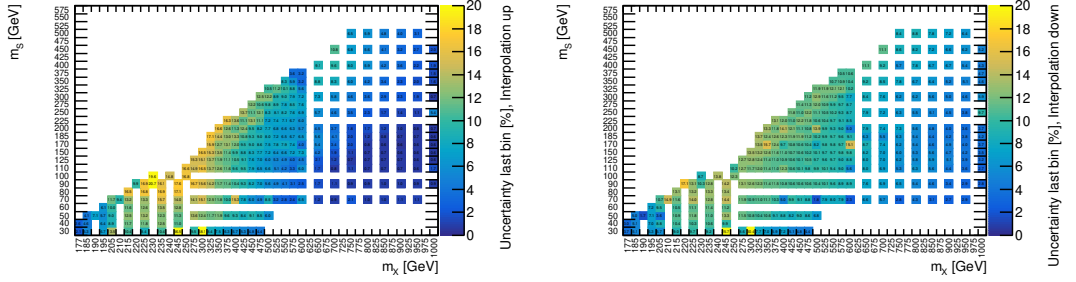


Fig. B.5: The up (left) and down (right) variations of the systematic uncertainty due to the interpolation method are displayed for the final bin of the PNN score in the $m_S - m_X$ plane.

It is important to note that this methodology is applicable only within the 2 b -tagged category, where the detector resolution of m_{jj} can be computed. Consequently, no interpolation is performed in the 1 b -tagged category. Additionally, the Lorentz transformation is effective only when sufficient neighboring points are available. This limitation explains why points close to the $m_S = m_X + 125$ GeV cannot be interpolated.

B.1.2.1 Signal Injection

Signal injection tests are conducted to determine the appropriate granularity for scans. For each injected signal, the cross section is approximately twice the expected limit. For $m_X < 300$ GeV (≥ 300 GeV), a 25 GeV (50 GeV) window in the (m_X, m_S) plane around the injected signal is analyzed. The expected significance from fitting the $\text{PNN}(m_X, m_S)$ distribution with the same m_X, m_S values as the injected signal is around 4σ . This granularity is considered adequate to ensure that no signal is missed if the expected significance at any neighboring point (m_X, m_S) is at least 3σ . Two examples of signal injection are shown in Figure B.6 and B.7 in Appendix B.1. These injection tests were also performed with other cross section values (1 fb and 0.1 fb instead of twice the expected limit) yielding similar results, reinforcing the granularity conclusions.

Figure B.6 presents an example of successful interpolation where the tested granularity is deemed sufficient. Conversely, Figure B.7 illustrates an instance where the interpolation is suboptimal. These findings suggest that additional points should be evaluated in the range $245 < m_X < 300$ GeV. The current pro-

posal includes interpolation for signals with $m_X = 275$ GeV, but signal injection tests indicate that finer granularity is necessary. Specifically, the PNN should be evaluated for $m_X = 260$ GeV (20 GeV from the last interpolated point with $m_X = 245$ GeV) and $m_X = 285$ GeV (1015 GeV from the nearest evaluated points with $m_X = 275, 300$ GeV). Lastly, Figure B.8 shows an example where the tested granularity exceeds the requirement. For $m_X > 600$ GeV, injection studies reveal that a 50 GeV granularity (as opposed to the current 25 GeV) is sufficient to detect any signal meeting the significance criteria ($Z \geq 3\sigma$).

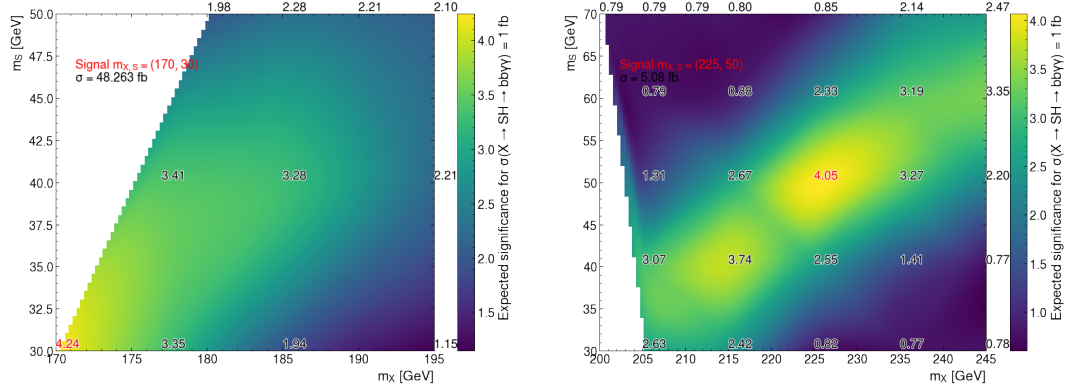


Fig. B.6: Expected significance for an injected signal with $m_{X,S} = (170, 30)$ GeV (left) and $m_{X,S} = (225, 50)$ GeV (right). The significance obtained from fitting the PNN (m_X, m_S) distribution using the same m_X, m_S values as the injected signal (referred to as the true signal) is shown in red. The expected significance at this point is approximately 4σ , as the cross-section for each injected signal is roughly twice the expected limit. Each plot displays the significance for m_X, m_S values within 25 GeV of the true signal.

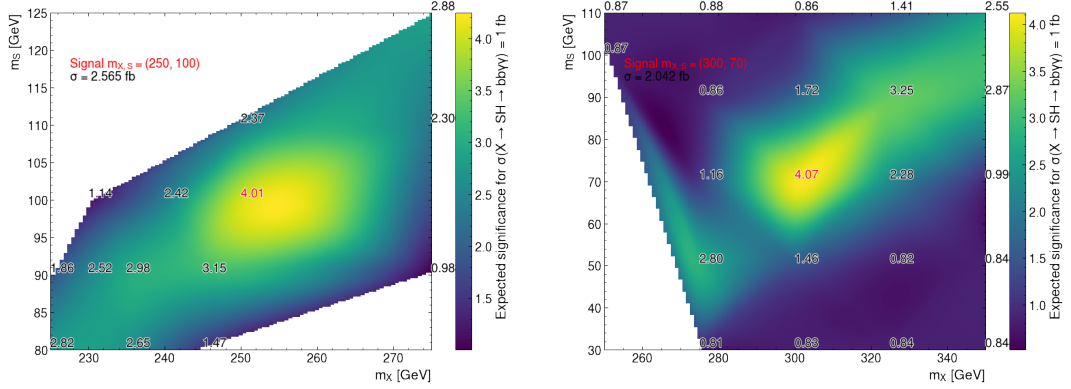


Fig. B.7: The expected significance for an injected signal with $m_{X,S} = (250, 100)$ GeV (left) and $m_{X,S} = (300, 70)$ GeV (right) is shown. The significance obtained from fitting the PNN (m_X, m_S) distribution using the same m_X, m_S values as the injected signal (referred to as the true signal) is highlighted in red. At this point, the expected significance is approximately 4σ , since the cross-section for each injected signal is about twice the expected limit. Each plot displays the significance for m_X, m_S values within 25 GeV of the true signal.

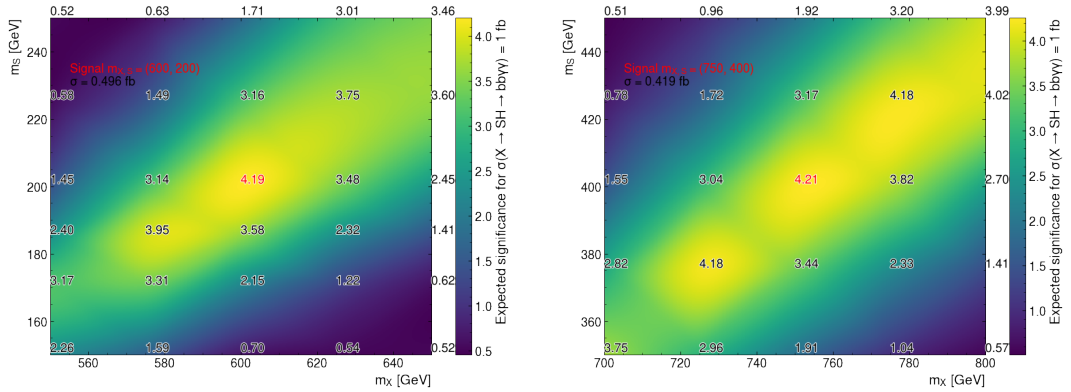


Fig. B.8: The expected significance for an injected signal with $m_{X,S} = (600, 200)$ GeV (left) and $m_{X,S} = (750, 400)$ GeV (right) is presented. The significance obtained from fitting the PNN (m_X, m_S) distribution using the same m_X, m_S values as the injected signal (referred to as the true signal) is highlighted in red. At this point, the expected significance is approximately 4σ , as the cross-section for each injected signal is about twice the expected limit. Each plot displays the significance for m_X, m_S values within 50 GeV of the true signal.

B.2 Blinded Results

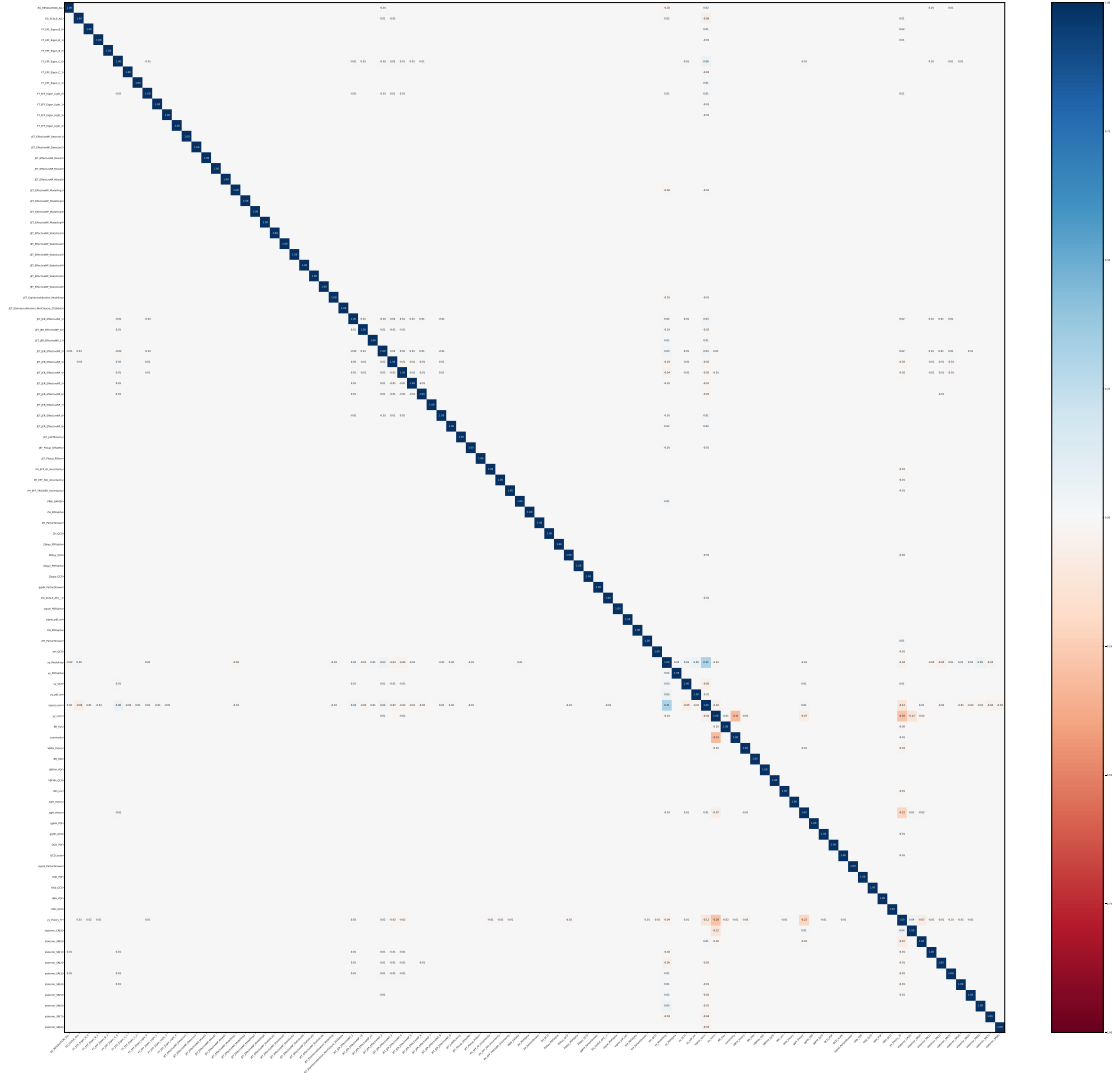


Fig. B.9: Correlation matrix for the PNN fit with $m_X = 250$ GeV and $m_S = 100$ GeV, derived from the Asimov dataset.

Table. B.2: Pre-fit and post-fit impact of the nuisance parameters to the POI for the PNN ($m_X = 250$ GeV, $m_S = 100$ GeV) fit. Impact is defined as the relative variation of the fitted POI when moving the NP value up/down by 1 sigma.

	pre-fit up (%)	pre-fit down (%)	post-fit up (%)	post-fit down (%)
signal_PartonShower	-8.934632	11.462310	-8.880633	11.378147
yy_theory_TF	-10.364250	11.253815	-7.536250	7.976481
EG_SCALE_ALL	-0.728839	4.787680	-0.723592	4.744087
signal_PDFalpha	-4.367982	4.690780	-4.340686	4.657583
yy_QCD	-2.145961	3.999937	-2.129457	3.965432
statererror_SR[7]	-3.871997	3.852646	-3.858729	3.837939
statererror_SR[8]	-3.406622	3.362080	-3.393947	3.348039
JET_JER_EffectiveNP_4	-4.640796	3.295826	-4.584182	3.250296
JET_JER_EffectiveNP_3	-5.047025	3.115979	-4.975129	3.065507
signal_pdf_set	-2.921657	2.926271	-2.903394	2.905565
BR_Hyy	-2.925801	2.863944	-2.907032	2.843138
yy_norm	0.000000	0.000000	-2.425787	2.456970
JET_EffectiveNP_Modelling1	-0.263718	2.188069	-0.262664	2.170980
JET_JER_EffectiveNP_6	-2.749400	2.001868	-2.725642	1.981983
PH_EFF_ID_Uncertainty	-2.336259	1.755678	-2.321416	1.742621
statererror_SR[6]	-1.860393	1.708893	-1.853127	1.701061
BR_Hbb	-1.765657	1.653621	-1.754790	1.641718
statererror_SR[5]	-1.795738	1.635407	-1.785232	1.624158
PH_EFF_ISO_Uncertainty	-1.970356	1.361913	-1.957927	1.351635
statererror_SR[2]	-1.274641	1.065064	-1.267841	1.058143
FT_EFF_Eigen_C_1	-0.990584	1.013811	-0.984268	1.005500
JET_JER_EffectiveNP_10	-1.746459	1.010368	-1.732949	1.000877
JET_EtaIntercalibration_Modelling	-0.518237	0.972779	-0.515378	0.964807
statererror_SR[4]	-1.038405	0.835936	-1.030906	0.828164
EG_SCALE_AF2__1	-0.412016	0.748700	-0.409896	0.742216
Luminosity	-0.953930	0.735593	-0.948329	0.729945
PH_EFF_TRIGGER_Uncertainty	-1.297043	0.654861	-1.289124	0.649549
JET_Pileup_OffsetMu	-0.273802	0.646347	-0.272740	0.640983
FT_EFF_Eigen_Light_1	-0.632368	0.609274	-0.628715	0.604048
FT_EFF_Eigen_B_1	0.524657	-0.509037	0.520088	-0.506295
FT_EFF_Eigen_C_2	0.582329	-0.570335	0.577410	-0.567194
statererror_SR[0]	0.441337	-0.657147	0.439499	-0.655324
FT_EFF_Eigen_Light_0	1.273357	-1.431366	1.261713	-1.420740
PRW_DATASF	0.982422	-1.576774	0.972985	-1.564722
JET_JER_EffectiveNP_9	1.094891	-1.685267	1.085626	-1.673411
JET_JER_EffectiveNP_8	1.079838	-1.824747	1.070366	-1.811497
FT_EFF_Eigen_C_0	3.701983	-3.484323	3.652699	-3.442745
FT_EFF_Eigen_B_0	4.211509	-3.863219	4.179211	-3.837155
JET_JER_EffectiveNP_1	3.439457	-4.548917	3.388924	-4.489907
JET_JER_EffectiveNP_2	4.112714	-6.768539	4.033360	-6.654020
yy_Modelling	38.302575	-21.602140	23.445348	-16.083056

Table. B.3: Pre-fit and post-fit impact of the nuisance parameters to the POI for the PNN ($m_X = 1000$ GeV, $m_S = 70$ GeV) fit. Impact is defined as the relative variation of the fitted POI when moving the NP value up/down by 1 sigma.

	pre-fit up (%)	pre-fit down (%)	post-fit up (%)	post-fit down (%)
signal_PDFalpha	-10.220212	13.077821	-10.156329	12.984052
signal_PartonShower	-9.060549	11.217989	-9.003451	11.138248
yy_Modelling	-19.787940	18.565316	-8.040840	7.959953
signal_pdf_set	-6.389834	7.361068	-6.348996	7.309907
ggH_theory	-3.148059	3.093782	-2.457930	3.035564
BR_Hyy	-2.947991	3.043200	-2.928103	3.021684
FT_EFF_Eigen_C_0	-2.399882	2.557577	-2.372665	2.527974
JET_JER_EffectiveNP_2	-3.218892	2.568458	-3.161799	2.523149
PH_EFF_ISO_Uncertainty	-1.415319	2.214953	-1.405984	2.199756
PH_EFF_ID_Uncertainty	-1.392752	2.188991	-1.383577	2.173983
JET_JER_EffectiveNP_1	-2.356550	2.007310	-2.327845	1.982719
BR_Hbb	-1.687372	1.748594	-1.676375	1.736742
PH_EFF_TRIGGER_Uncertainty	-0.805961	1.571722	-0.800702	1.561001
yy_QCD	-2.829368	1.411275	-2.805365	1.398971
yy_PDFalpha	-1.385127	1.368539	-1.374496	1.357680
staterror_SR[6]	-1.326844	1.320459	-1.326833	1.320447
EG_SCALE_ALL	1.699010	1.212613	1.684113	1.201945
VBFH_theory	-0.932651	0.950042	-0.918223	0.949958
Luminosity	-0.847560	0.860838	-0.842258	0.854990
yy_pdf_set	-0.861690	0.842436	-0.855128	0.835692
EG_SCALE_AF2__1	0.837029	0.764051	0.831271	0.758781
JET_JER_EffectiveNP_9	-0.544412	0.664772	-0.540640	0.659907
EG_RESOLUTION_ALL	1.751095	0.611654	1.738155	0.607056
staterror_SR[5]	-0.561975	0.535057	-0.560601	0.533661
staterror_SR[2]	-0.473440	0.444318	-0.471549	0.442406
FT_EFF_Eigen_C_2	-0.052873	0.380964	-0.052621	0.378276
JET_JER_EffectiveNP_7	-0.369114	0.350885	-0.366740	0.348406
FT_EFF_Eigen_B_0	-0.024077	0.344875	-0.024019	0.342446
staterror_SR[3]	-0.320660	0.290483	-0.319009	0.288819
staterror_SR[0]	0.334765	-0.336212	0.333949	-0.335538
JET_JER_EffectiveNP_10	0.354907	-0.376656	0.352391	-0.374216
JET_Pileup_OffsetMu	0.248518	-0.469836	0.246729	-0.466772
JET_JER_EffectiveNP_6	0.707377	-0.729444	0.702319	-0.724476
FT_EFF_Eigen_Light_1	1.069218	-0.738416	1.061446	-0.733278
yy_norm	0.000000	0.000000	0.821051	-0.748670
FT_EFF_Eigen_C_1	1.381583	-1.056701	1.371007	-1.048917
FT_EFF_Eigen_Light_0	1.581983	-1.216979	1.570605	-1.208560
FT_EFF_Eigen_B_1	1.760875	-1.384100	1.748744	-1.374949
JET_EtaIntercalibration_Modelling	0.397481	-1.387501	0.394439	-1.377425
JET_EffectiveNP_Modelling1	0.549014	-1.398544	0.544806	-1.388288
JET_JER_EffectiveNP_4	2.235163	-2.676771	2.202253	-2.637455
JET_JER_EffectiveNP_3	2.037753	-2.732095	2.009951	-2.694963

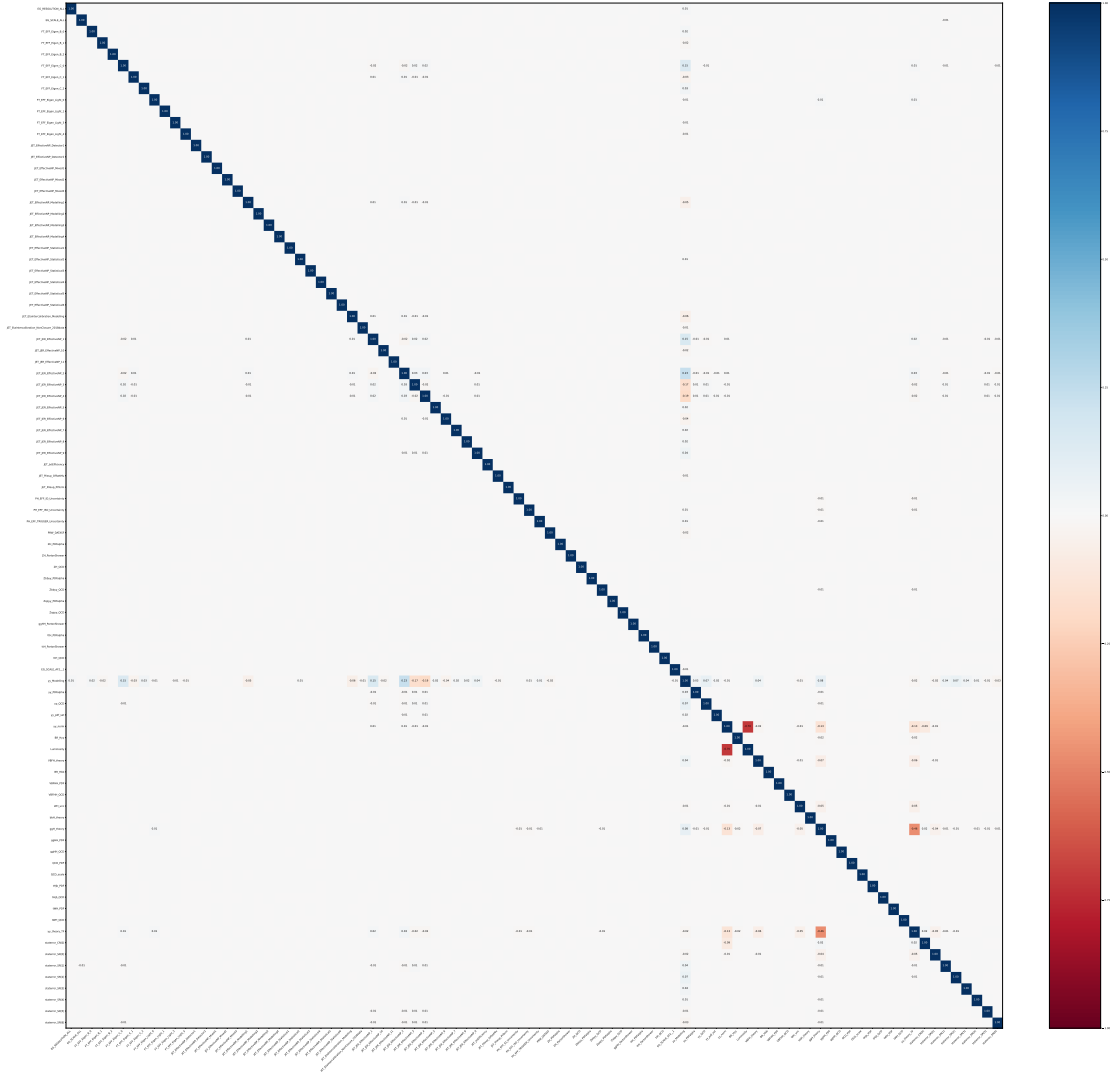


Fig. B.10: Correlation matrix for the PNN fit with $m_X = 1000$ GeV and $m_S = 70$ GeV, derived from the Asimov dataset.

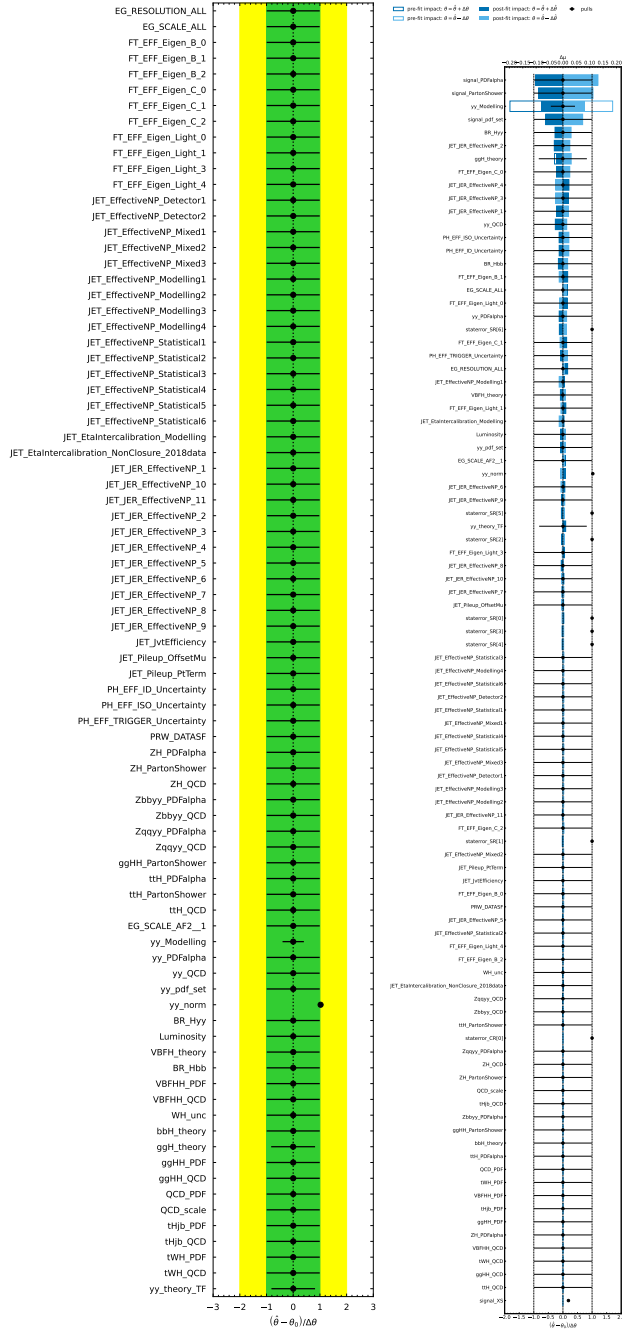


Fig. B.12: The pull of the fit parameters (left) and the nuisance parameters ranked by their impact on the parameter of interest (POI) (right) are presented for the PNN fit with $m_X = 1000$ GeV and $m_S = 70$ GeV. The fit is performed using the Asimov dataset. The signal_norm represents the POI, while yy_norm refers to the $\gamma\gamma$ +jets normalization factor, derived from the fit to data in the sideband (SB) region.

B.3 Unblinded Results

The SR distributions corresponding to the PNN input variables are shown in Figure B.13, B.14 and B.15.

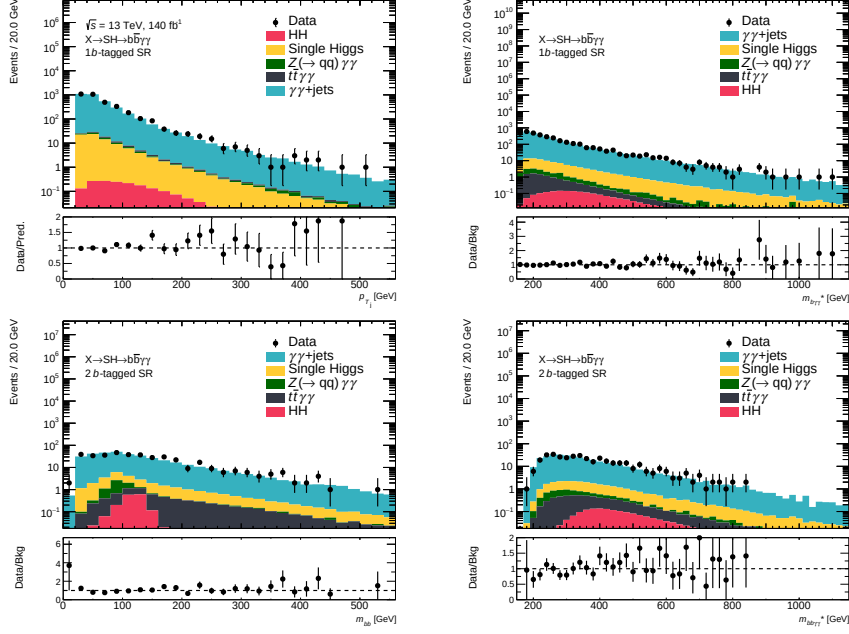


Fig. B.13: The unblinded signal region (SR) distribution for the input variables of the 1 b -jet PNN is shown at the top, and the 2 b -jet PNN distribution is displayed at the bottom.

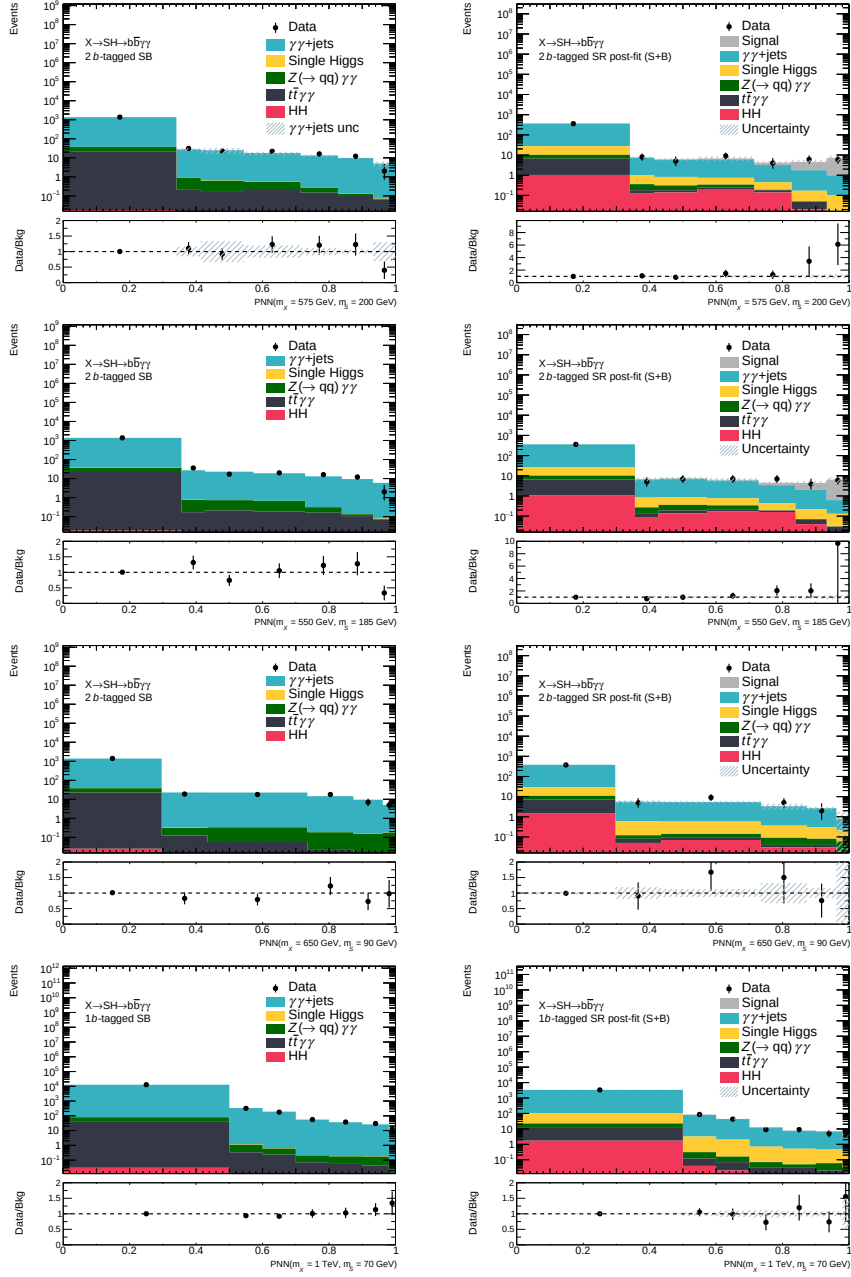


Fig. B.14: The post-fit sideband (SB) distributions (left) and signal region (SR) distributions (right) are presented for the PNN with $m_X = 575$ GeV and $m_S = 200$ GeV, and PNN with $m_X = 550$ GeV and $m_S = 185$ GeV, where a small excess is observed. Also shown are the PNN distribution for $m_X = 650$ GeV and $m_S = 90$ GeV, where CMS previously reported a small excess, and the PNN distribution for $m_X = 1$ TeV and $m_S = 70$ GeV, where no excess is detected.

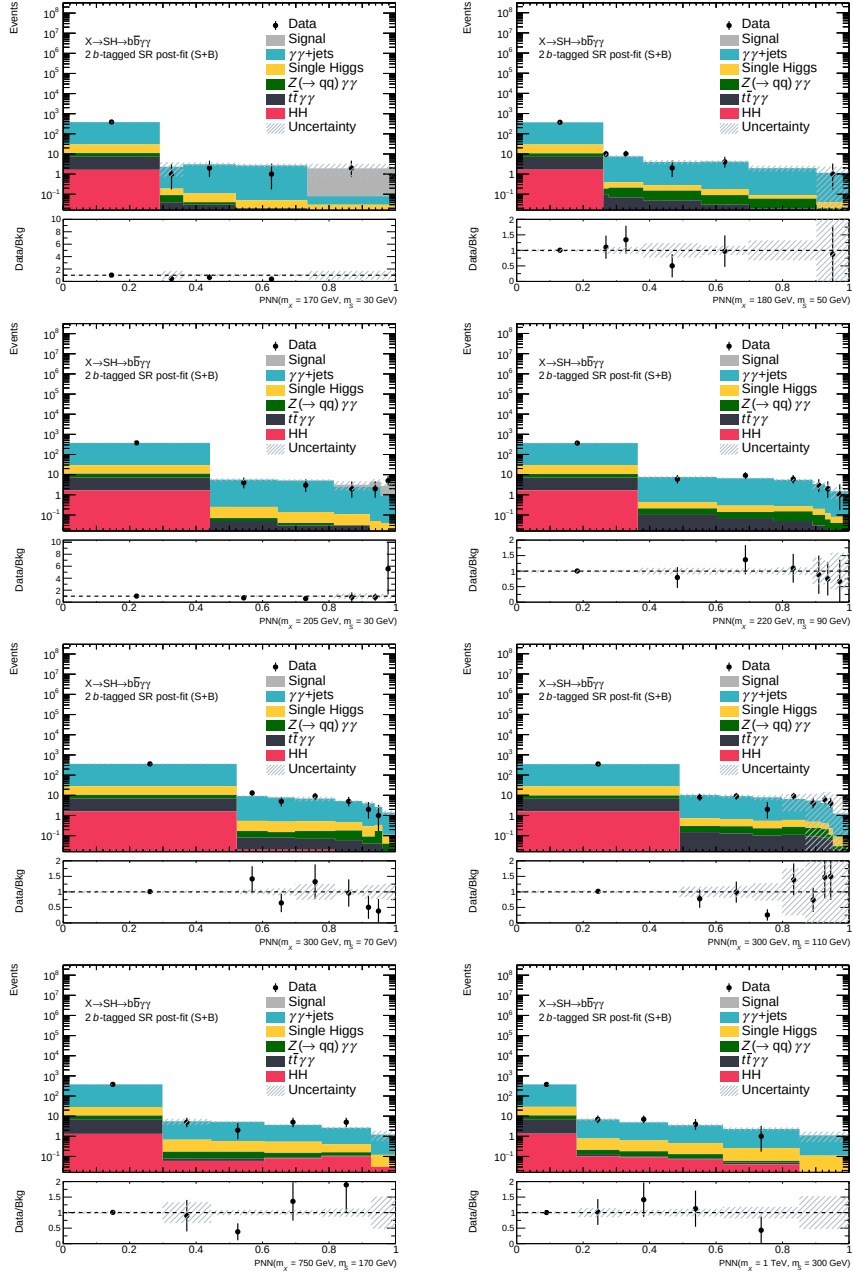


Fig. B.15: The signal plus background post-fit signal region (SR) distributions are shown for a subset of (m_X, m_S) values within the 2 b -tagged region. These points correspond to MC signals that are available for analysis.

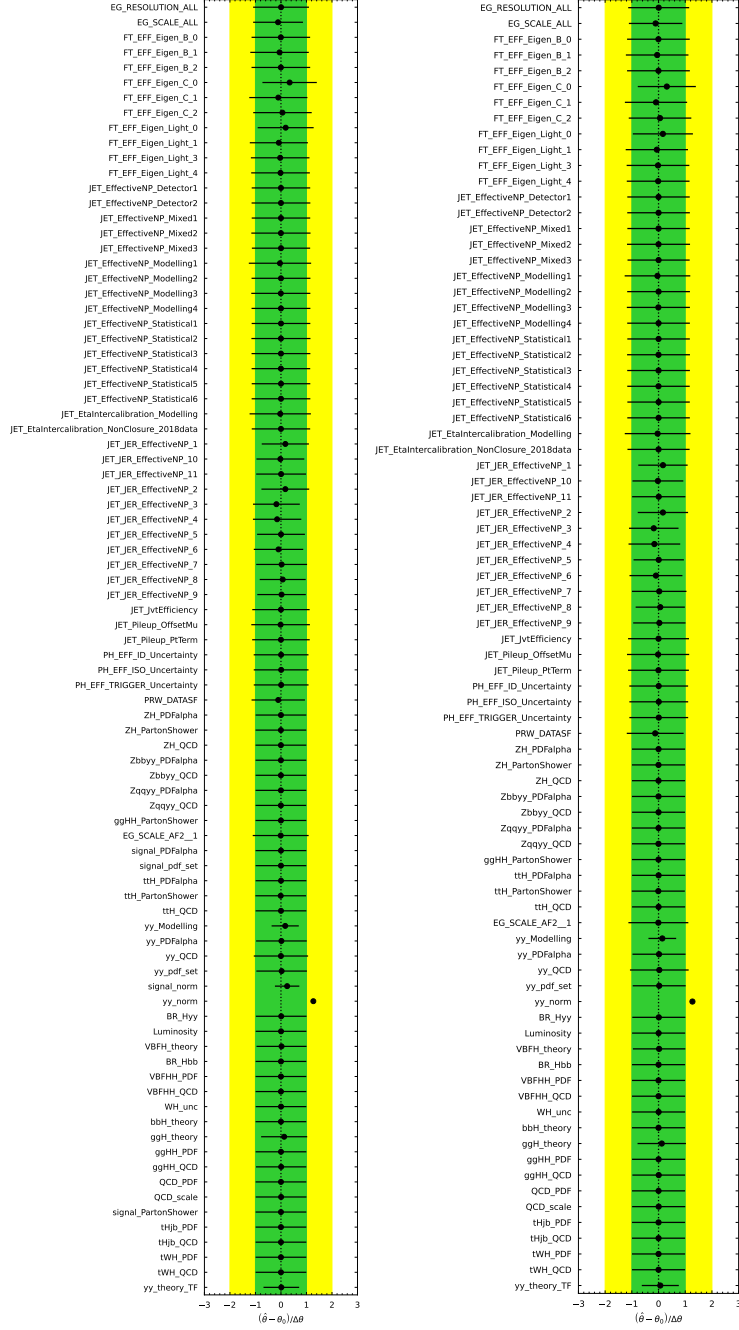


Fig. B.16: The pull distribution is shown for the signal plus background fit (left) and the background-only fit (right) for $m_X, m_S = (250, 110)$ GeV in the 2 b -jet region.

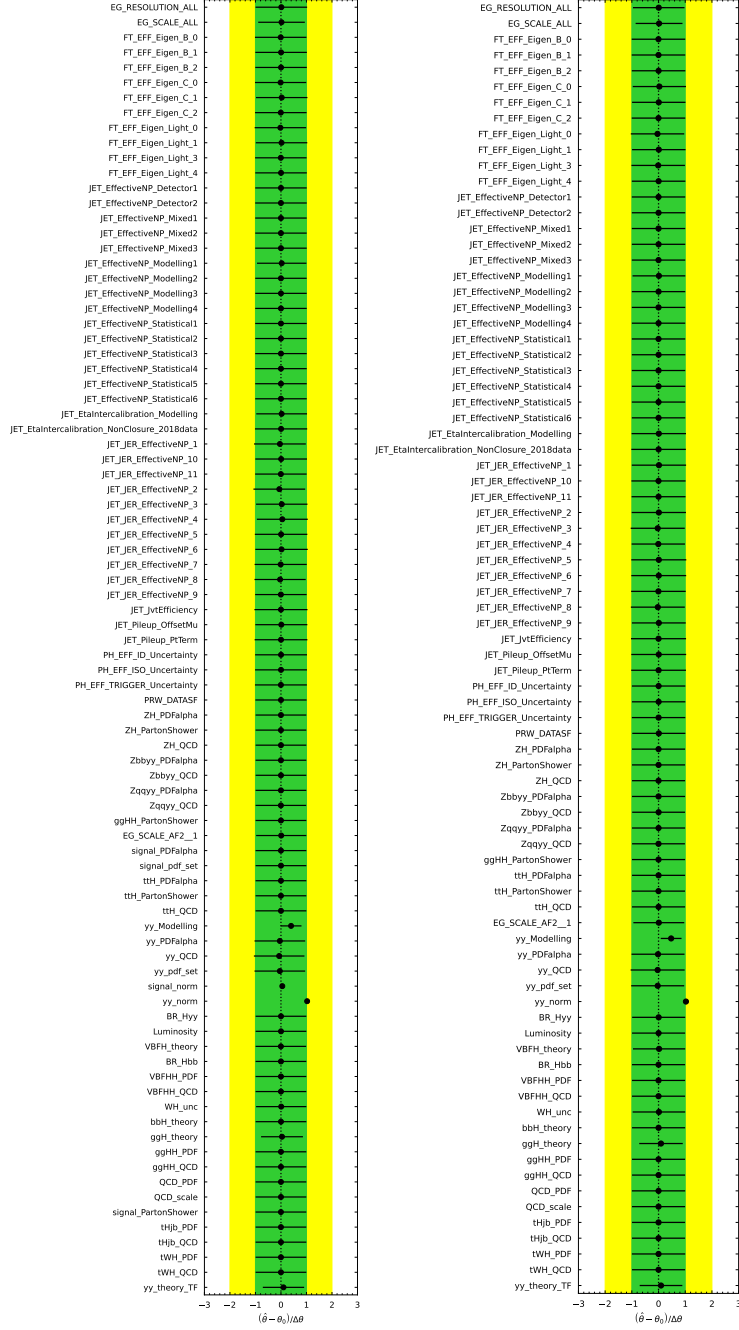


Fig. B.17: The pull distribution is displayed for the signal plus background fit (left) and the background-only fit (right) for $m_X, m_S = (1000, 70)$ GeV in the 1 b -jet region.

附录 C

Resistive Plate Chamber Study

C.1 Introduction

Resistive Plate Chambers (RPCs) have been a fundamental component in particle physics experiments since their development in the 1980s. Their successful application in major experiments such as ATLAS at CERN, CMS, and ALICE has demonstrated their versatility and robustness. Beyond CERN, RPCs have been utilized in astrophysics experiments like ARGO-YBJ and neutrino physics experiments, including Daya Bay. Additionally, RPCs have proven useful in various non-particle physics applications, such as Time-of-Flight Positron Emission Tomography (PET/CT) and even volcanic tomography.

The appeal of gaseous detectors like RPCs lies in their remarkable features, including spatial resolutions on the order of a centimeter and time resolutions in the nanosecond range. Their durability, ease of construction, and cost-efficiency further enhance their suitability for both particle detection and triggering in high-energy physics experiments. Moreover, RPCs are not limited to traditional uses; they have also been adapted for calorimetric measurements, particularly for applications in high-performance calorimetry based on the Particle Flow Algorithm (PFxA).

Looking forward, RPCs are anticipated to play a significant role in next-generation particle detectors. They are being considered for use in the Semi-Digital Hadronic Calorimeter (SDHCAL) at the International Linear Collider (ILC) and the Circular Electron Positron Collider (CEPC), reflecting their continued relevance in advancing particle detection technologies. This adaptability, combined with their proven performance, positions RPCs as a cornerstone technology in both current and future high-energy physics research.

C.2 The ATLAS RPC Phase-II Upgrade for High Luminosity LHC

The Resistive Plate Chamber (RPC) detectors within the ATLAS Muon Spectrometer play a pivotal role in triggering events involving muons in the central region of the detector. With the transition towards the High-Luminosity Large Hadron Collider (HL-LHC) program, these detectors are undergoing a significant upgrade to meet the increased demands of particle detection and data collection.

The existing RPC system, which currently consists of six cylindrical detector layers, provides full spatiotemporal localization of particle hits. However, this structure will be expanded with the installation of 306 new triplets of next-generation RPCs, specifically within the innermost regions of the muon barrel spectrometer. By increasing the number of tracking layers from 6 to 9, the trigger lever arm will be effectively doubled, enabling a substantial enhancement of trigger redundancy. This upgrade is expected to improve the muon detection coverage from approximately 76% to 96%, a critical increase for high-precision event detection.

A key feature of this upgrade is the introduction of an advanced integration of front-end electronics within the detector's Faraday cage. This innovation significantly reduces the average charge per event, thus allowing the RPC system to handle higher rates of particle events while maintaining longevity and reliability. The new chambers will also incorporate optimized materials and thickness, utilizing a 1 mm gas gap and 1.4 mm resistive electrodes, which replaces the previous 1.8 mm thickness. These changes not only fit within the limited space available in the ATLAS inner barrel but also enhance the detector's rate capability.

In addition, the front-end electronics will include a precise Time-to-Digital Converter (TDC) that provides a time resolution of 100 ps. The anticipated time resolution of a single 1 mm RPC gas gap will be around 300 ps. This improvement opens the possibility for a stand-alone Time-of-Flight measurement, which will significantly impact ATLAS's ability to search for massive, long-lived particles, a key focus of the HL-LHC program.

Overall, the ATLAS RPC Phase-II Upgrade is poised to make a considerable contribution to the detector's performance, particularly in addressing the challenges posed by the higher luminosity environment of the HL-LHC. The completion of this upgrade will play a crucial role in ensuring that the ATLAS detector remains at the forefront of particle physics research.

C.3 RPC Design and Gas Flow Simulations

For proper operation of the RPCs, it is essential to maintain a continuous gas flow at an appropriate rate to prevent the buildup of contaminants and rad-

icals. These contaminants, formed by the interaction of radicals in the gas with the chamber materials, can degrade the detector’s performance. Ensuring uniformity in the gas flow and preventing deformation of the electrode plates are critical factors for achieving optimal detector performance. We employed detailed simulations to optimize the design of the RPCs. Using COMSOL Multiphysics® version 5.4 as the simulation platform, a finite element method was applied to simulate the gas flow field, the deformation of electrodes, and the electric field distribution within the RPC.

C.3.1 Design and Geometry of the RPC

The structure of the glass RPCs is composed of two glass sheets, each with dimensions of $1 \times 1 \text{ m}^2$, where the anode has a thickness of 0.7 mm, and the cathode has a thickness of 1.1 mm. The gap between these electrodes is maintained at 1.2 mm, with cylindrical nylon spacers of 8 mm diameter providing the necessary support. Silicone-based glue is used to seal the chamber, and the walls are made of FR4 material.

The gas flow system is designed with inlets and outlets placed at opposite corners on the same side of the chamber. The gas inlet features two pipes, while the outlet has four pipes, which prevent overpressure from accumulating inside the chamber. Additionally, two gas guides made from PEEK, each with six perforated holes, are located 2 cm from the chamber walls along both the inlet and outlet sides. This configuration ensures uniform gas distribution throughout the chamber. Figure C.1 shows the cross-sectional schematic of the RPC.

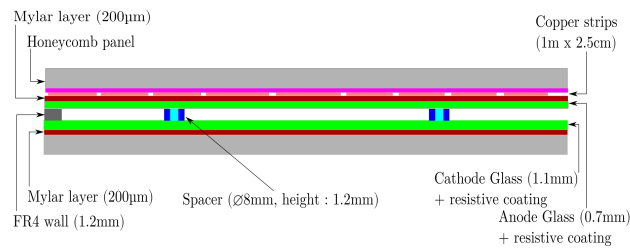


Fig. C.1: Schematic cross-section of the glass Resistive Plate Chamber (RPC), not to scale.

C.3.2 Spacer Design and Distribution

Spacers are crucial for maintaining the uniformity of the gas gap thickness, though they present an obstacle for gas diffusion. Two configurations of spacer distributions have been proposed. The first configuration, called the “Reference

spacers” setup, consists of a grid of 10×10 aligned spacers, with a total of 100 spacers, as shown in Figure C.2a. The second configuration, referred to as “Shifted spacers”, includes four spacers on odd rows and five on even rows, resulting in 76 spacers in total, as depicted in Figure C.2b.

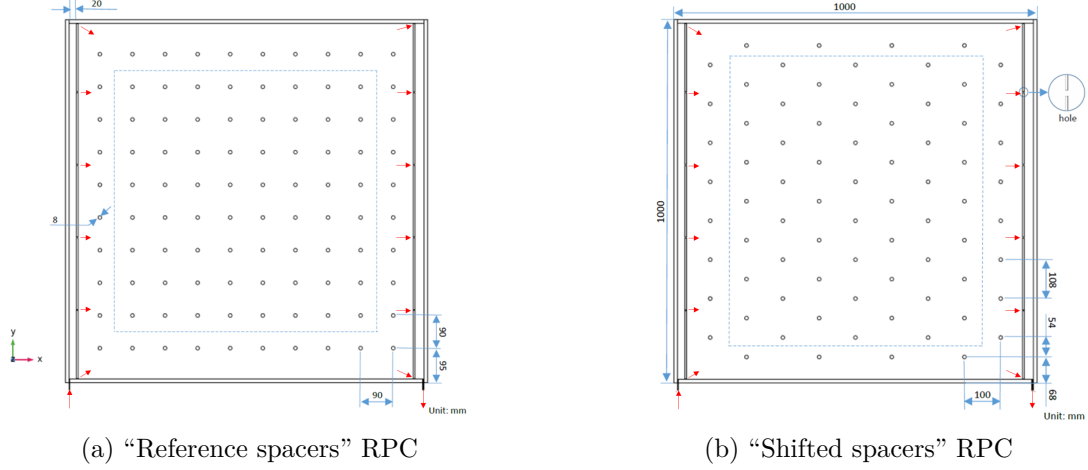


Fig. C.2: Diagram of $1 \times 1 \text{ m}^2$ RPCs with two distinct spacer configurations. The dashed lines indicate the central region of the chamber used for comparing gas velocity and vorticity.

C.3.3 RPC Construction

The construction of RPCs requires a controlled, clean environment to ensure the precision and integrity of the components. In order to avoid contamination and maintain the quality of the detector assembly, all RPCs are constructed in a cleanroom facility. This ensures that sensitive components such as electrodes and spacers are handled in a dust-free environment, reducing potential errors during the manufacturing process. Figure C.3 shows the cleanroom where the RPC assembly takes place.

Following the simulation outcomes, both “Reference” and “Shifted” RPC models were successfully assembled in a clean room with dimensions of $1 \times 1 \text{ m}^2$. The construction process, illustrated in Figure C.4, follows these steps:

- Secure the spacers, walls, and PEEK bars onto the 1.1 mm electrode using adhesive.
- Attach the spacers and walls onto the 0.7 mm electrode, applying silicone along the chamber’s edges.
- Apply a graphite coating (a mixture of conductive graphite diluted with lacquer) on the glass surface using a spray gun.
- Cover the graphite-coated glass with $200 \mu\text{m}$ mylar films.



Fig. C.3: Cleanroom facility utilized for the assembly of RPC detector components.

- Fix the power connectors on both sides of the chamber and fasten the mylar films with adhesive tape.

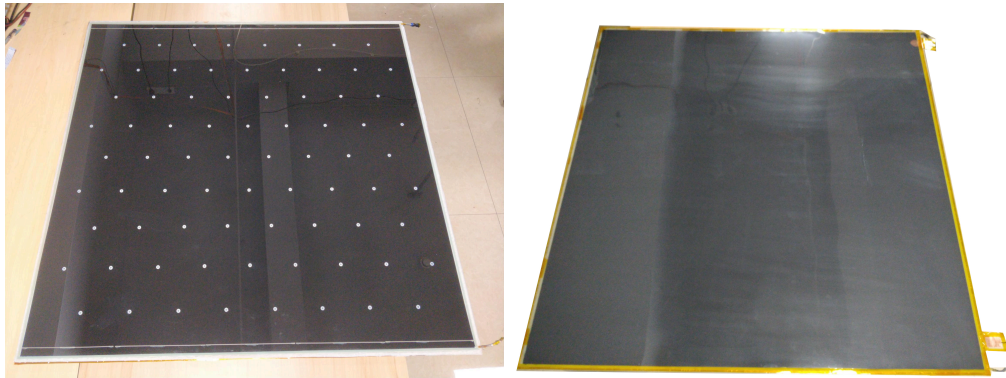


Fig. C.4: Assembly of the glass RPC with a “shifted spacers” configuration.

C.3.4 Cosmic Muon Test Platform

Signals generated by cosmic muons in the glass RPC are collected on the cathode electrode, which is covered with a 3 mm thick foam panel embedded with copper strips of 2.5 cm width. The signal from one side of each strip is amplified using a Front-End Board (FEB) with a gain of approximately 16. The amplified signals are then digitized by a CAEN V172 module at a sampling rate of 5 GS/s. The opposite end of each strip is grounded through a $20\ \Omega$ resistor, which helps match the impedance of the strip panel and prevents signal reflections.

The triggering system consists of four scintillators, each measuring $40 \times 20\text{ cm}^2$. Two scintillators are positioned on both sides of the RPC chamber to achieve signal coincidence. A visual representation of the cosmic muon test system is

shown in Figure C.5.



Fig. C.5: Configuration of the cosmic muon test system.

C.3.5 Data Taking and Analysis

We analyzed how the detection efficiency of the RPC changes with applied high voltage, which ranged from 5700 V to 7000 V, in steps of 100 V. For this, cosmic muon events were detected using scintillators as triggers. For each recorded event, the digitized output of all eight readout strips, as well as the scintillator trigger, were stored. The efficiency (ϵ) of the RPC for detecting muons is determined using the following expression:

$$\epsilon = \frac{N_{\text{signal}}}{N_{\text{triggered}}} \quad (\text{C.1})$$

where N_{signal} refers to the number of events where the RPC signal was present, and $N_{\text{triggered}}$ is the total number of events triggered by scintillators. Figure C.6 displays an event with a single detected signal (red curve). To compute the average noise B and RMS noise σ_B (~ 0.9 mV), the 20 ns interval before the 40 ns wide signal region was used.

The results of the efficiency versus applied voltage are displayed in Figure C.7. The performance of the “Shifted spacer” chamber was compared with that of the “Reference spacers” chamber, showing very similar trends. Notably, both chambers reached a plateau in efficiency exceeding 95%. No corrections for variations in temperature or atmospheric pressure were applied, which largely explains the observed shift. This indicates that the new RPC design with fewer spacers still delivers comparable muon detection efficiency.

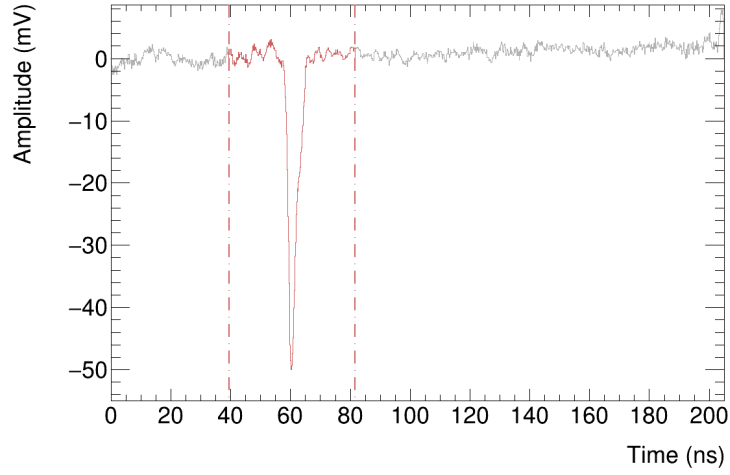


Fig. C.6: An event displaying a single signal track (red curve).

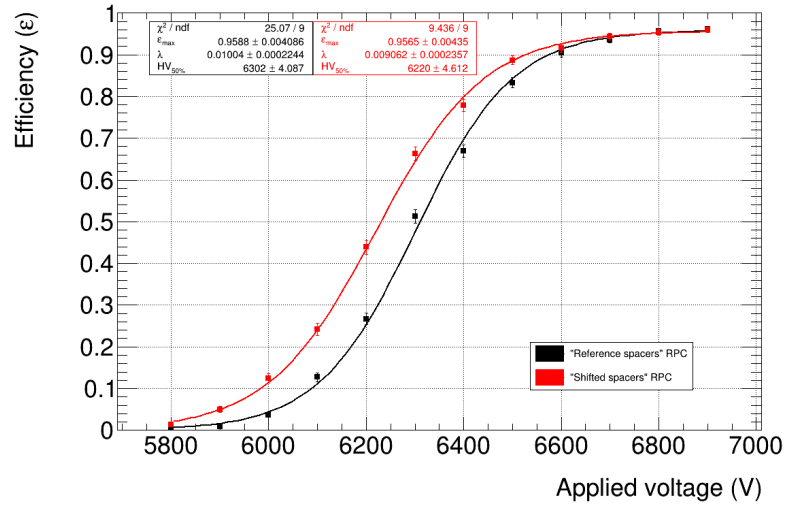


Fig. C.7: Efficiency as a function of applied voltage for RPCs with “Reference spacers” and “Shifted spacers” configurations.

C.4 RPC Tests at CERN

C.4.1 RPC Trolley Setup

The RPC trolley plays a crucial role in moving and preparing the RPCs for conditioning. High-voltage (HV) cables are now correctly connected, and the RPC trolley has been relocated to the Gif++ facility for conditioning tests. The RPC setup has been elevated for better positioning, and buffering material has been added below to ensure stability during testing. The images in Figure C.8 show the trolley setup.

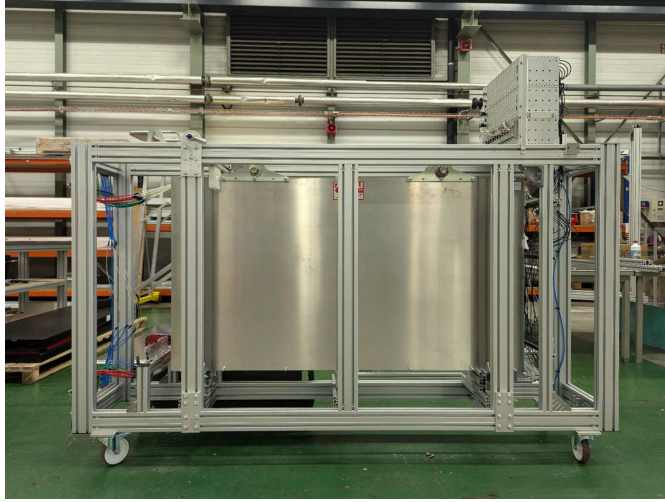


Fig. C.8: RPC trolley setup showing the raised structure and cable connections.

C.4.2 RPC Conditioning

The conditioning process of the RPCs uses a Cs-137 photon source, which initiates particle showers and avalanches. The conditioning focuses on the BIS chambers (1 mm thick, 24 chambers in total) to improve their performance by reducing defects and impurities. In this test, the resistivity of the chambers is measured by applying different source shielding values (multipliers of 1, 3.3, and 100). The gas inputs and electronics of the system are carefully monitored during the conditioning process. Figure C.9 shows the setup used for RPC conditioning.

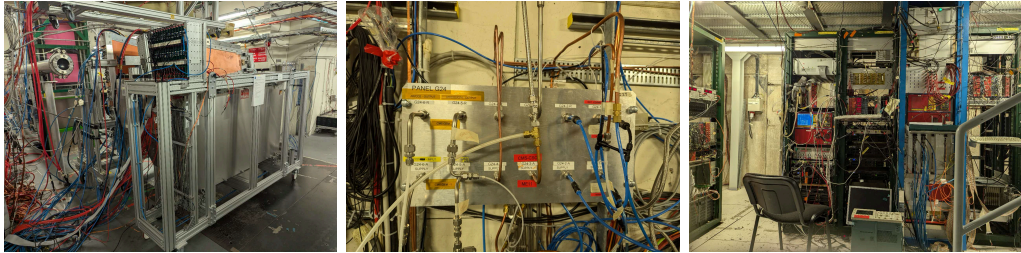


Fig. C.9: RPC conditioning setup with photon source and shielding for defect reduction. RPC platform, gas inputs and electronics are shown in the figures.

C.4.3 RPC HV Scan

An HV scan was conducted at the BB5 facility without source to measure the response of RPC channels under different voltage conditions. The current was recorded using a multimeter, and it was observed that some channels (e.g., BIS2B 14/24) exhibited higher currents than expected, with a few channels showing steeper current increases. Another scan was performed at the Gif++ facility, with the results monitored by the DCS system. Figures C.10 and C.11 display the

results from the scans.

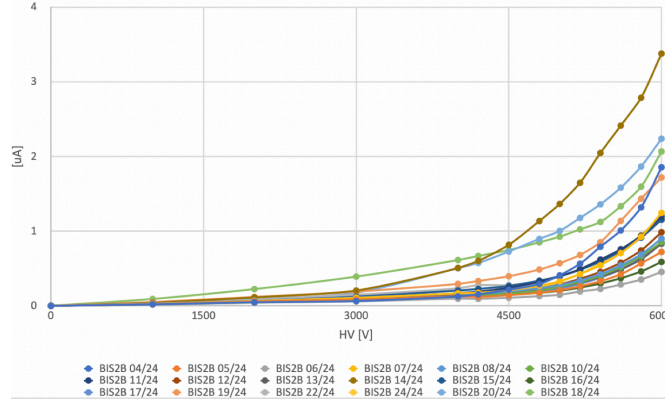


Fig. C.10: Results of the high-voltage scan showing current versus applied voltage, tested at the BB5 facility

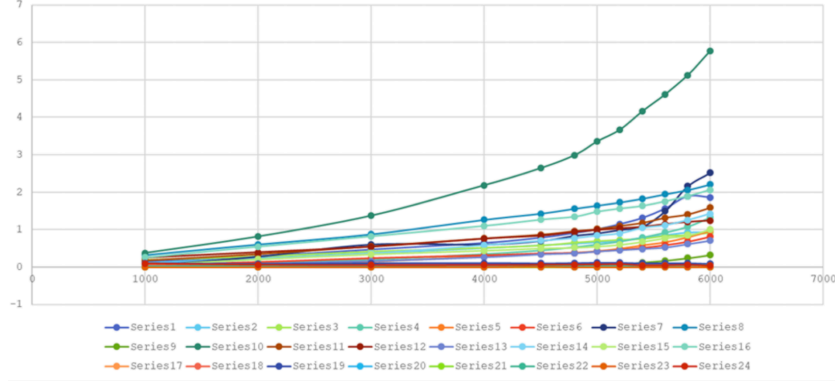


Fig. C.11: Results of the high-voltage scan showing current versus applied voltage, tested at the Gif++ facility.

C.4.4 Gas Composition Study

A study on gas composition was conducted to investigate the optimal gas mixture for the RPCs, while also addressing environmental concerns such as gas leakage and global warming. The chamber used in the test had dimensions of 50 cm by 50 cm and a 2 mm gas gap. The standard gas mixture, initially 94% $C_2H_2F_4$, was gradually replaced with a mixture of 64% $C_2H_2F_4$ and 30% CO_2 . The study measured parameters such as cluster size, efficiency, time of flight (TOF), and voltage thresholds. The gas chamber and system setup are shown in Figure C.12.

C.5 Conclusion

Resistive Plate Chambers have been essential in particle physics experiments due to their reliability and adaptability, being utilized in experiments like ATLAS,



Fig. C.12: Gas composition study showing the setup for gas flow and chamber monitoring.

CMS, and ALICE, as well as in medical and astrophysical applications. Their high spatial and temporal resolution makes them well-suited for current and future high-energy physics experiments, such as those at the ILC and CEPC.

The ATLAS RPC Phase-II upgrade addresses the demands of the High-Luminosity LHC by expanding the RPC system and improving its efficiency and longevity. Through optimized designs, materials, and advanced electronics, the system is prepared to handle the increased particle rates while maintaining high detection precision. Simulation studies and cleanroom construction have ensured uniform gas flow and mechanical stability, critical for the detector's long-term performance.

Extensive tests, including cosmic muon tests, data analysis under varying voltage, and HV scans at CERN, have validated the enhanced design of the RPCs. These tests confirmed the system's ability to maintain high detection efficiency and stability, even with reduced spacers or modified gas compositions. These improvements ensure that the ATLAS RPCs will remain at the forefront of particle detection technology as we enter the next phase of high-energy physics experiments.

附录 D

Data Quality for ATLAS RPC Detector Control System (DCS)

D.1 Introduction

The Resistive Plate Chamber (RPC) Detector Control System (DCS) is an integral part of the ATLAS experiment, tasked with monitoring and controlling the operations of the RPC subsystem within the ATLAS muon spectrometer. The RPC DCS is responsible for managing a vast number of detector components, ensuring the safe and effective functioning of tens of thousands of channels across multiple subsystems.

The RPCs in the ATLAS detector are gas-based detectors, which are designed to provide fast and accurate muon triggers in the barrel region of the ATLAS detector. They operate under challenging conditions, including high magnetic fields and significant radiation levels, requiring the DCS to maintain precise control over power supplies, high and low voltage settings, currents, and thresholds, as well as trigger electronics.

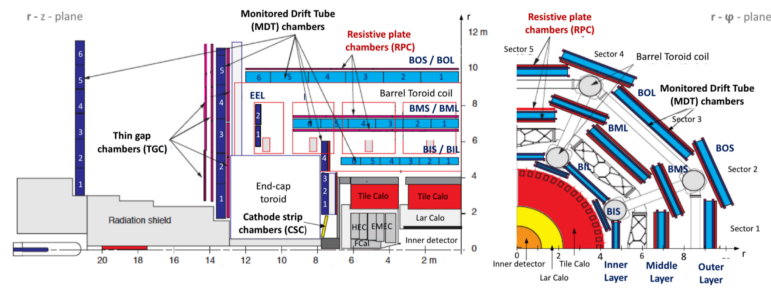


Fig. D.1: A schematic illustration of the RPC system in the ATLAS experiment is shown. The detector is divided into 16 sectors along the ϕ direction and 6 stations along the η direction on both the A and C sides of the detector.

D.1.1 Functions of the RPC DCS

The primary functions of the RPC DCS include:

- **Monitoring and Controlling Subsystems:** The DCS monitors the high and low voltage power supplies, trigger electronics, currents, thresholds, environmental sensors, and gas systems that are critical to the operation of the RPCs.
- **Abstraction Layer for Ease of Operation:** The DCS provides an abstraction layer that simplifies the management of complex detector operations, enabling operators to execute expert actions and analyze archived data efficiently.
- **Data Archival:** Operational data, such as the voltages, currents, and environmental parameters, are archived for later analysis, ensuring that the system's performance can be tracked over time and any issues can be identified and addressed.
- **Interfacing with Other ATLAS Systems:** The RPC DCS interacts with other control systems within the ATLAS detector, such as the global detector control system (GCS) and trigger and data acquisition (TDAQ) systems, ensuring seamless communication and synchronization between subsystems.

D.1.2 RPC Detector Specifics

The RPCs cover a surface area of approximately 4000 m² and contain a gas volume of about 18 m³. Given the strong magnetic fields and the presence of high radiation in the ATLAS cavern, the RPC DCS must ensure the continued operation of power and control items distributed across the detector. The DCS handles the control of components, such as the high voltage (HV) and low voltage (LV) supplies, ensuring that the RPC system operates within its required parameters.

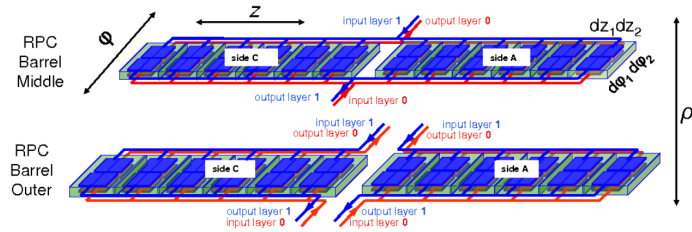


Fig. D.2: Gas distribution.

D.1.3 Error Detection and Data Quality

One of the key functions of the RPC DCS is to ensure data quality during the operation of the ATLAS detector. The DCS continuously monitors parameters like high voltage, low voltage, current draw, and trigger rates, and is capable of automatically delivering data quality flags to ensure the detector's health. The information is collected and stored in the ATLAS Oracle database, where it can be analyzed for accurate data-taking conditions and for detecting possible hardware failures during data acquisition.

In conclusion, the RPC DCS is vital for the safe, efficient, and reliable operation of the RPC subsystem within the ATLAS detector, ensuring that the system operates under optimal conditions for accurate muon detection and triggering.

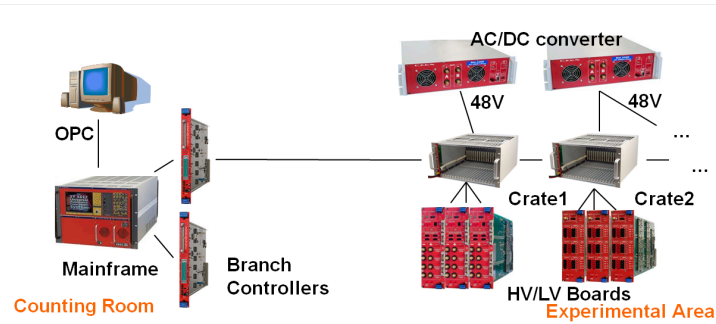


Fig. D.3: The layout of DCS (Detector Control System) machines and hardware.

D.2 Matching Analysis of RPC DCS Parameters

This section presents the analysis of key RPC DCS (Resistive Plate Chamber Detector Control System) parameters, focusing on the correlation between gas gap currents, high-voltage (HV) settings, and offline measurements such as RPC efficiency. The purpose of this analysis is to identify RPC panels that exhibit mismatches between their DCS parameters and offline measurements, which may indicate underlying issues that need attention, such as improper threshold settings or problematic gas gaps.

The tables below provide a detailed breakdown of the matching and mismatching parameters for various RPC sector types, including those where current and HV settings align, those with only current or only HV, and panels with discrepancies in efficiency measurements.

Table. D.1: Matching of RPC DCS gas gap currents and high voltages

Sector type	Number of matching between current and hv	Number with only current but no hv	Number with only hv but no current
BML	1250 (1287)	0	0
BMS	720 (1200)	0	0
BOL	768	0	0
BOS	576	0	0
BME	8 (16)	0	0
BMF	88 (176)	0	0
BOE	8	0	0
BOF	192	0	0
BOG	104	0	0
Total	3714 (4327)	0	0

Table. D.2: Matching of RPC DCS gas gap currents and offline RPC efficiency measurements

Sector type	Number of matching between current and efficiency	Number with only current but no efficiency	Number of only efficiency but no current
BML	1217 (1237)	33 (50)	0
BMS	528 (1007)	192 (193)	24
BME	16	0	0
BMF	176	0	0
BOL	768	0	0
BOS	576	0	0
BOE	4	4	4
BOF	192	0	0
BOG	64	40	40
Total	3541 (4040)	269 (287)	68 (1.5%)

Table. D.3: Matching of RPC DCS threshold voltages and offline RPC efficiency measurements

Sector type	Number of matching between Vth and efficiency	Number of panels with Vth but not efficiency	Number of panels with efficiency but not Vth
BML	2094	148 (304)	380
BMS	2062	0	0
BME	32	0	0
BMF	352	0	0
BOL	1536	0	0
BOS	1152	0	0
BOE	16	0	0
BOF	384	0	0
BOG	192	16 (32)	8 (32)
Total	7820	164 (320)	388 (412)

D.3 Correlation Between Gas Gap Currents, Efficiency, and High Voltages

This section presents the correlation between RPC gas gap currents and two key parameters: efficiency and high-voltage (HV) settings. The analysis aims to identify any mismatches or patterns that may indicate inefficiencies or malfunctioning panels within the RPC system.

D.3.1 Correlation Between Gas Gap Currents and Efficiency

Figures D.4 through D.5 illustrate the relationship between gas gap current (I_{gap}) and offline efficiency measurements for different sector types (BML, BMS, BOL, and BOS). The goal of this analysis is to investigate how the gas gap current influences the efficiency of the RPC panels in various sectors.

The efficiency is calculated using the formula:

$$E \approx 1 - (1 - \text{Eff}_\eta)(1 - \text{Eff}_\phi)$$

where Eff_η and Eff_ϕ represent the efficiencies in the eta and phi directions, respectively. Panels with low gas gap currents (e.g., $I_{gap} < 0.5 \mu\text{A}/\text{m}^2$) or low efficiency ($\text{Eff} < 0.05$) in each sector were investigated and compiled into several lists.

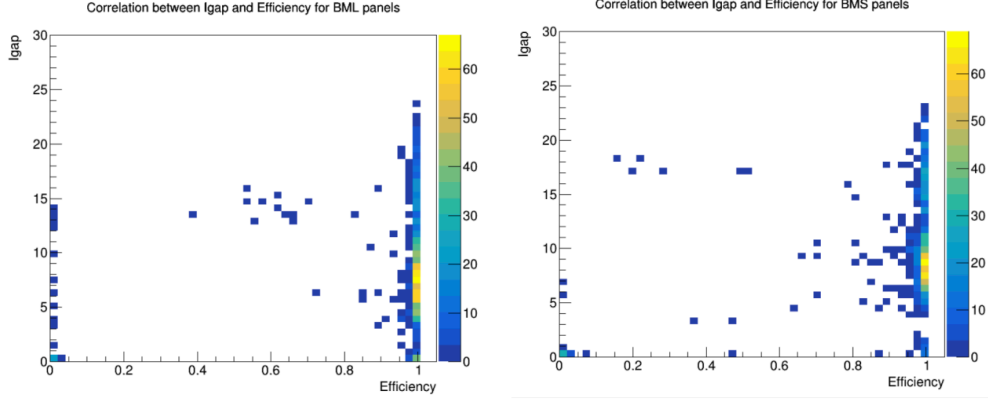


Fig. D.4: Correlation between I_{gap} and efficiency for BML and BMS panels.

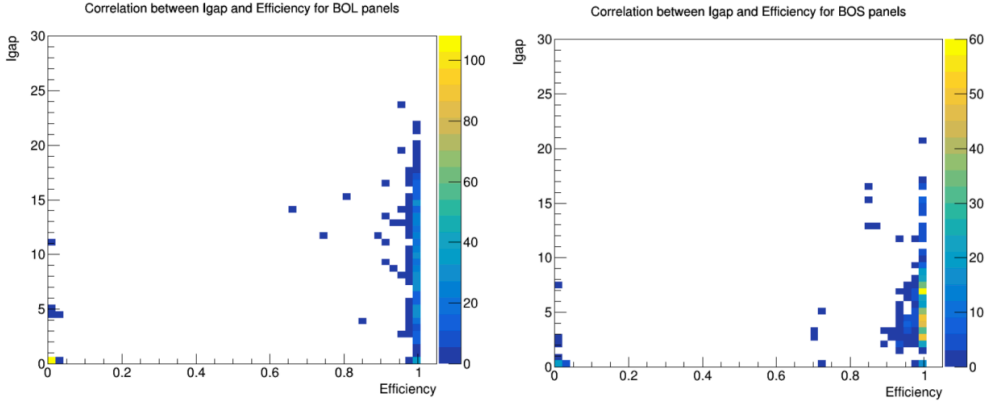


Fig. D.5: Correlation between I_{gap} and efficiency for BOL and BOS panels.

D.3.2 Correlation Between Gas Gap Currents and High Voltages

Figures D.6 through D.7 demonstrate the relationship between gas gap current (I_{gap}) and high-voltage (HV) settings for various sector types. The analysis shows that for most chambers, there is good matching between the DCS (Detector Control System) parameters and offline measurements. However, certain panels show discrepancies, such as 5–10% of chambers and 0–5% of panels where matching cannot be performed.

Key observations from this analysis include:

- BML, BMS, BOL, BOS: $HV > 9500V$, $I_{gap} < 1 \mu A/m^2$
- BOL: $HV < 9500V$ (indicating potential mismatches)

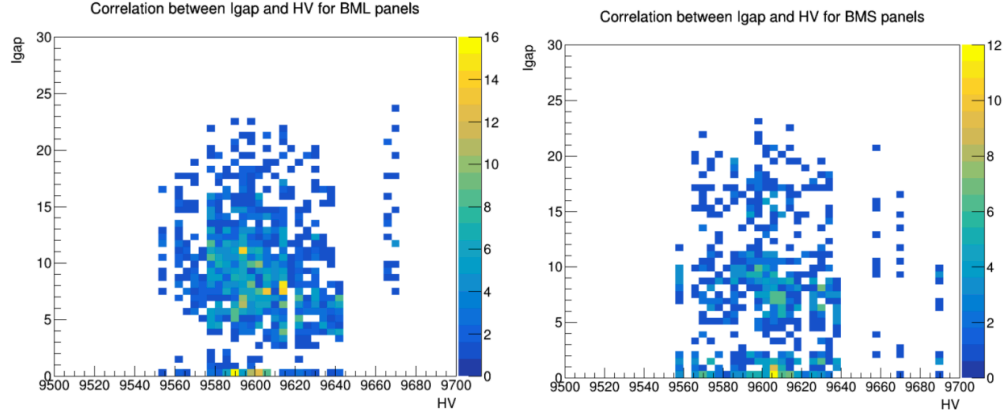


Fig. D.6: Correlation between I_{gap} and HV for BML and BMS panels.

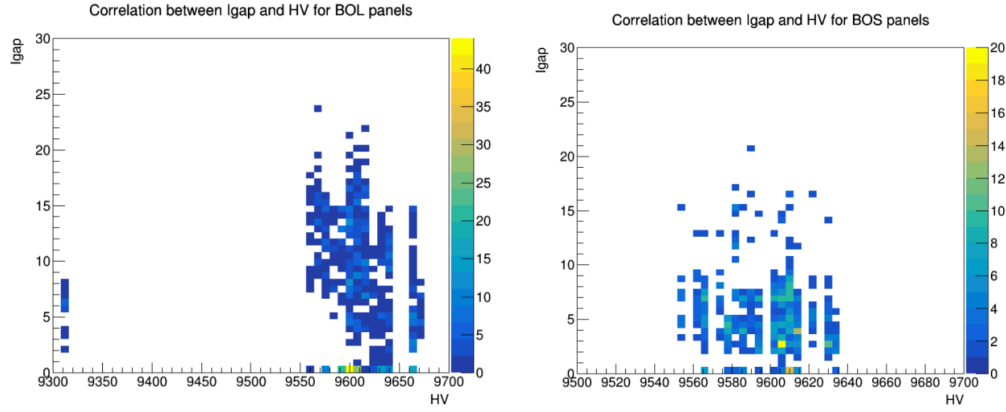


Fig. D.7: Correlation between I_{gap} and HV for BOL and BOS panels.

Overall, the matching analysis provides insight into the performance and reliability of the RPC system, helping to identify potential areas for improvement in both DCS settings and offline data correlation.

D.4 Data Extraction from DDV Server

This section provides a detailed overview of the data extraction procedure from the ATLAS DDV server for Runs 364292 and 363979. The extracted dataset includes gas gap currents, high voltage (HV) values, and other critical sensor readings essential for the Resistive Plate Chamber (RPC) performance analysis. The process employs a Python-based script to retrieve the necessary data from the DDV server, as illustrated on the right-hand side of the slide.

For each run, the extraction begins by executing specific commands to fetch gas gap currents, HV data, and relevant sensor parameters. The commands specify

the data range (e.g., corresponding to a particular run) and the type of data to extract (e.g., currents, HV, or sensor readings). Following extraction, the data are plotted and compared across multiple runs to assess consistency and validate the RPC system's performance during the data-taking periods.

Key resources supporting this workflow include:

- Twiki Page: A comprehensive guide on RPC HV data extraction and analysis is available at the [PhysicsRPCHVScan Twiki page](#).
- Analysis Framework: The plotting and analysis framework for RPC DCS data is accessible via the [PlotRPCDCS GitLab repository](#).
- Results Portal: The extracted data and analysis outcomes are available on the [DDVWeb results portal](#).

In conclusion, the DDV server is the primary repository for accessing and analyzing RPC DCS data. The workflow described in this section facilitates a systematic comparison and validation of key detector parameters across multiple runs, ensuring the operational reliability of the RPC system within the ATLAS experiment.

D.5 Analysis of Gas Gap Currents, High Voltages, Temperature, and Humidity in RPC Systems

This section provides an in-depth analysis of gas gap currents, high voltages (HV), temperature, and humidity within the RPC system, utilizing data extracted from the DDV server. The analysis focuses on Runs 364292 and 363979, highlighting both normal and anomalous behaviors observed across different panels and sensors. Such analysis is critical for maintaining the optimal performance of the RPC system, identifying potential issues requiring further investigation, and enhancing overall detector reliability.

Figure D.8 illustrates the custom-built webpage, developed using PHP, designed to facilitate the comparison of Detector Control System (DCS) variables between two distinct runs. This tool simplifies the process of comparing essential parameters such as gas gap currents, HV, temperature, humidity, and gas flow across multiple runs. By offering side-by-side graphical representations of these variables, the webpage enables users to quickly spot discrepancies or unusual patterns between runs, assisting in the rapid identification of potential RPC system issues.

This feature is particularly valuable when comparing a run exhibiting normal behavior to one showing abnormal patterns, making it easier to isolate and address potential performance issues in the RPC system. Through this streamlined pro-

cess, the tool significantly aids in the monitoring and assessment of the detector's operational status, ensuring consistency and early detection of problems.

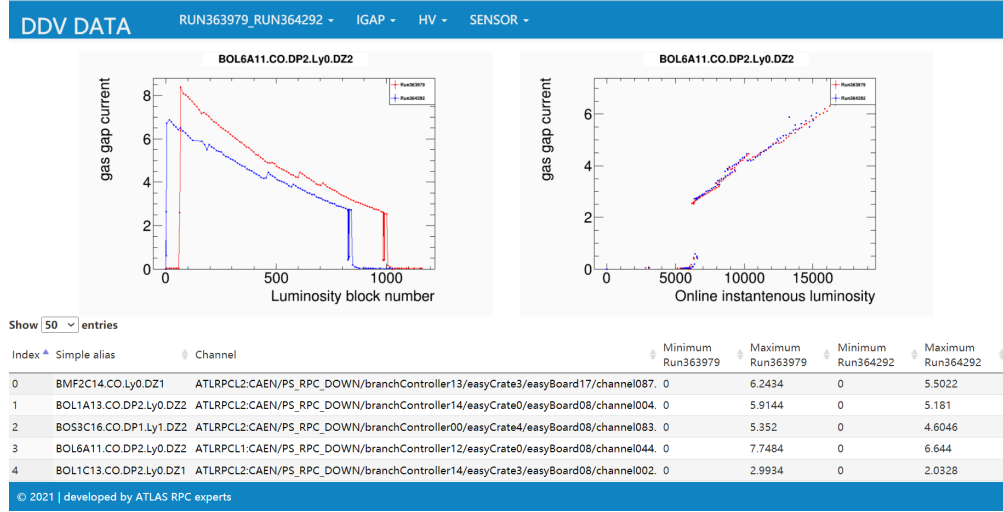


Fig. D.8: Comparison of gas gap currents between two runs in the website.

D.5.1 Gas Gap Currents Comparison in Two Runs

Figure D.8 also presents a comparison of gas gap currents between Run 364292 and Run 363979. The plots illustrate the relationship between gas gap currents and luminosity block numbers across various channels, enabling a clear visualization of the current behavior during different phases of the runs. This comparison helps in identifying any deviations or correlations that may indicate potential issues with the RPC system.

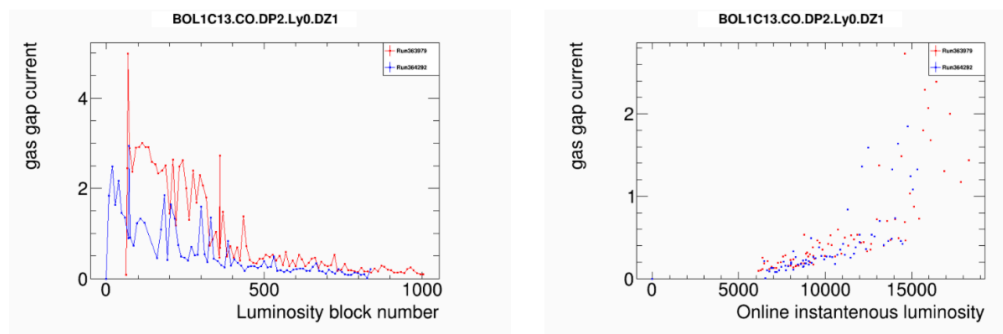


Fig. D.9: Abnormal cases for gas gap currents.

Figure D.9 highlights instances of abnormal gas gap current behavior, which could signal potential issues within the RPC system requiring further investigation. Such anomalies, including variations in current behavior between runs, may indicate inconsistencies in detector performance or external environmental influences.

Additionally, a custom webpage has been developed to display these results, providing a detailed interface for users to explore the gas gap current behavior under varying conditions. This tool enables a more thorough examination of the data, assisting in the identification of patterns or irregularities that may impact the RPC system's performance.

D.5.2 High Voltage (HV) Analysis

The high voltage (HV) behavior plays a critical role in ensuring the stable operation of the RPC system. This section examines the HV values recorded during Runs 364292 and 363979, aiming to identify both typical and abnormal patterns.

Figure D.10 illustrates normal HV behavior, where the voltage remains consistently stable around the expected levels throughout the luminosity block range. This stability is key to maintaining reliable detector performance, as any significant deviations could affect the efficiency of the RPC system.

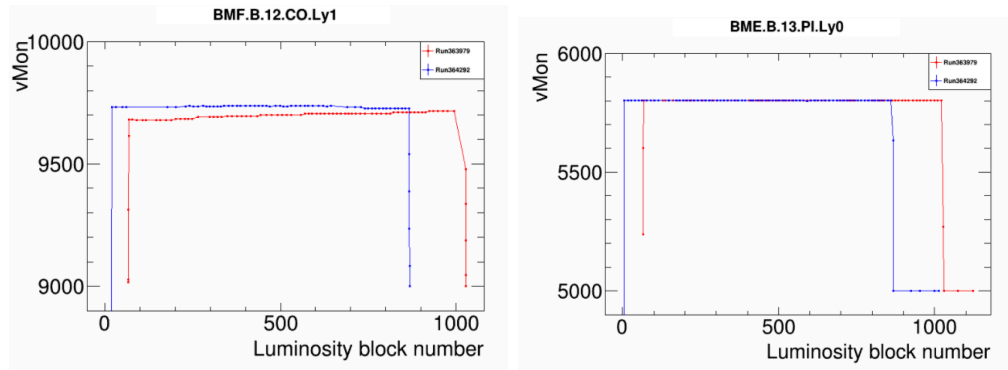


Fig. D.10: Normal HV behavior in Runs 364292 and 363979 across different luminosity block numbers. Stability in HV is observed, indicating proper system operation.

Figure D.11 highlights instances of abnormal HV behavior observed in certain panels during the runs. These deviations from the expected voltage levels may indicate potential hardware malfunctions or external environmental factors that could impact the overall performance of the detector. Identifying such irregularities is crucial for diagnosing and addressing issues to maintain the RPC system's operational stability.

D.5.3 Temperature Analysis

Temperature stability is a critical factor for the reliable performance of the RPC system. This section analyzes the temperature behavior during Runs 364292 and 363979, identifying both normal and abnormal instances.

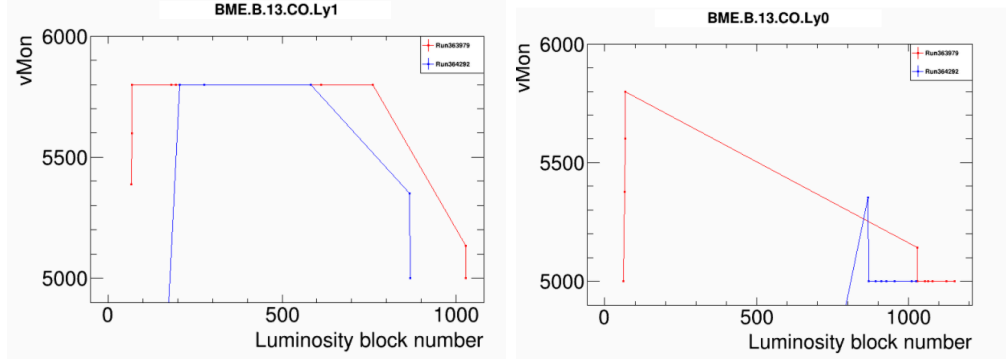


Fig. D.11: Abnormal HV behavior showing deviations from the expected values, potentially indicating hardware or environmental issues.

Figure D.12 shows the normal temperature behavior, where the system consistently maintains temperatures within the expected range. This stability is essential for ensuring the detector functions under optimal conditions, minimizing the risk of temperature-related performance issues.

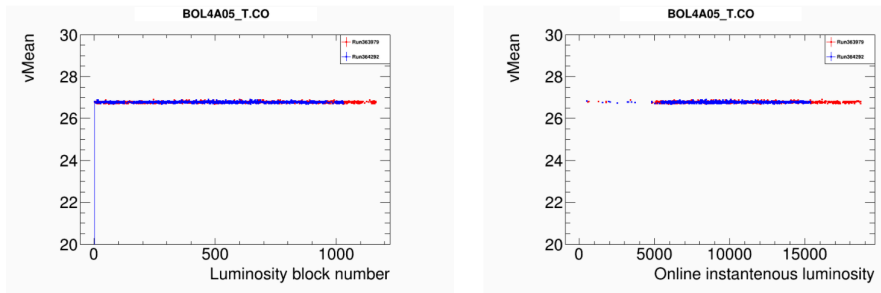


Fig. D.12: Normal temperature behavior in Run 364292 and Run 363979. The temperatures remain stable and within expected limits throughout the run.

Figure D.13 presents abnormal temperature readings. Deviations from the expected temperature range may point to potential issues such as malfunctioning sensors or environmental fluctuations, which could negatively impact the system's efficiency and stability. Identifying and addressing these anomalies is crucial for maintaining optimal detector performance.

D.5.4 Relative Humidity Analysis

Figure D.14 displays the relative humidity measurements for Run 364292. Humidity is a crucial parameter for the operation of RPC detectors, as it directly influences the gas mixture and, if not properly regulated, could lead to inefficiencies or even damage to the system. The figure shows that humidity values remain within the expected range, indicating normal operational conditions throughout the run.

In cases of abnormalities, these could be attributed to sensor malfunctions, gas

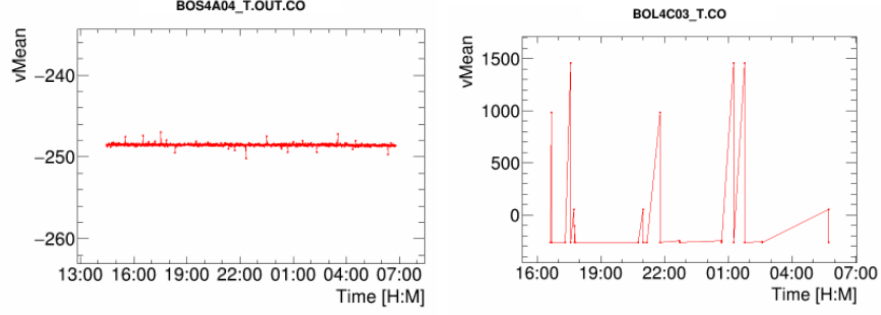


Fig. D.13: Abnormal temperature behavior showing significant deviations from expected values, which may negatively impact detector performance.

flow issues, or external environmental factors that require further investigation. The detailed data can be explored on the associated website, providing further insights into these conditions.

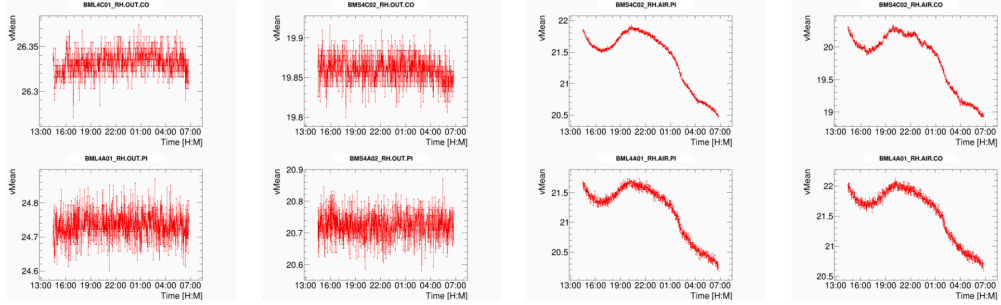


Fig. D.14: Relative humidity in Run 364292 demonstrates normal behavior on both the left and right panels. The humidity levels remain stable and within the expected range, ensuring proper conditions for the RPC system during the run.

D.5.5 Gas Flow Analysis

Gas flow is another critical parameter for ensuring the proper functioning of the RPC system. Figure D.15 presents the gas flow measurements for Run 364292, showing normal flow patterns, with the flow remaining stable throughout the run.

Prompt attention to any abnormal gas flow behavior is essential, as such issues can greatly affect the detector's efficiency and overall performance. Detailed results of the gas flow measurements can be further explored on the website for comprehensive analysis and monitoring.

D.6 RPC DCS Data Extraction for New Runs

This section outlines the process of extracting RPC DCS data for new runs using the PhysicsRPCPlot framework. This framework streamlines the analysis of RPC performance by providing tools to retrieve run data from the COOL database

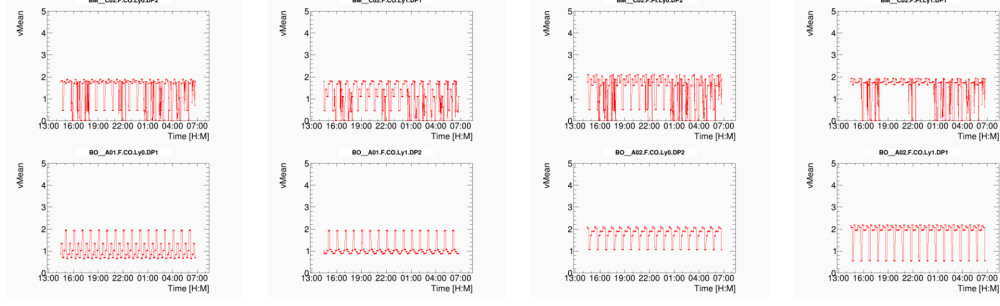


Fig. D.15: Gas flow in Run 364292 displays normal behavior, as illustrated here. The flow remains stable and within expected ranges, ensuring the optimal functioning of the RPC system throughout the run.

and configure the environment for efficient data processing.

To initiate the process, users must set up the environment by configuring the appropriate software release and integrating with the ATLAS Athena framework. Once the setup is complete, the framework enables the extraction of run data, including essential performance metrics such as gas gap currents, high voltage, and sensor readings. This allows for the effective tracking and comparison of RPC performance across different runs.

For detailed setup instructions and guidelines, users can refer to the Physic-sRPCPlot Twiki page. This framework is crucial for the ongoing analysis of RPC systems, simplifying the data extraction and processing for new ATLAS runs, and ensuring consistent monitoring of RPC detector performance.

D.7 Summary of RPC DCS Work

The work conducted on the ATLAS RPC DCS system focuses on developing advanced tools and techniques to enhance the monitoring and analysis of RPC detector performance. By evaluating key parameters such as gas gap currents, front-end (FE) thresholds, high voltage (HV) settings, and environmental factors like gas flow and temperature, the project seeks to identify and mitigate potential inefficiencies within the system.

A core aspect of this work involves correlating DCS parameters with offline measurements of gas gap efficiency, particularly using muon candidates. This correlation helps to detect discrepancies between expected and actual performance, allowing the identification of panels with mismatched properties, which can then be investigated and rectified.

Moreover, the development of automated scripts and tools has greatly streamlined the extraction and comparison of RPC DCS data. A custom-built website, integrated with the ATLAS DDV server, facilitates the efficient presentation and analysis of thousands of parameters across multiple runs. This is further sup-

ported by scripts designed to automatically extract and plot DCS parameters for each run, providing data quality (DQ) experts with critical insights for identifying and resolving data quality issues.

In summary, the work on RPC DCS data extraction and analysis significantly improves RPC system monitoring, enabling more effective tracking of detector performance. This contributes to enhancing the stability and reliability of the RPC system within the ATLAS experiment.

LIST OF PUBLICATIONS

Publications with Major Contributions in the ATLAS Collaboration

1. ATLAS Collaboration, Fiducial and differential cross-section measurements of electroweak $W\gamma jj$ production in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector, Published by The European Physical Journal C (EPJC)
2. ATLAS Collaboration, Search for a new resonance decaying into a scalar and a Higgs boson in the final state with two bottom quarks and two photons in proton-proton collisions at $\sqrt{s} = 13$ TeV, Published by Journal of High Energy Physics (JHEP)

Publications on Detector R&D

1. Performance study of large-area glass resistive plate chambers with different spacer configurations, Journal of Instrumentation, Vol. 16, P12022 (December 2021), DOI: 10.1088/1748-0221/16/12/P12022.
2. Scintillator tile batch test of CEPC AHCAL, Journal of Instrumentation, Vol. 17, P05006 (May 2022), DOI: 10.1088/1748-0221/17/05/P05006.

CONFERENCE AND SEMINAR PRESENTATIONS

- [1] Measurements of vector-boson scattering with the ATLAS experiment

Prague, Czech, 42nd International Conference on High Energy Physics, July 20, 2024

- [2] Measurement of $4ljj$ production using 140 fb⁻¹ of proton-proton collision data at $\sqrt{s} = 13$ TeV with the ATLAS detector

Prague, Czech, 42nd International Conference on High Energy Physics, July 18, 2024

- [3] Search for a resonance decaying into a scalar particle and a Higgs boson in the final state with two bottom quarks and two photons in proton-proton collisions with ATLAS

Bordeaux, France, the 15th Workshop of France China Particle Physics Laboratory, June 11, 2024

- [4] Search for a heavy scalar X decaying to a scalar S and a Higgs boson in $X \rightarrow S(b\bar{b})H(\gamma\gamma)$ channel in the ATLAS experiment

Zhuhai, China, the 14th Workshop of France China Particle Physics Laboratory, November 7, 2023

- [5] Observation and cross section measurements of electroweak $W(\rightarrow l\nu)\gamma jj$ in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector

Nanjing, China, the 8th China LHC Physics Workshop, November 24, 2022

- [6] Search for new scalar X in the $X \rightarrow S(b\bar{b})H(\gamma\gamma)$ channel

Paris, France, Workshop Physics ATLAS France 2022, September 20, 2022