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**Measurement of the production cross
section of a single top quark in
association with a Z boson at the ATLAS
detector**

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Abstract

This thesis focuses on one of the rarest *top* quark processes, the electroweak single *top* quark production in association with a *Z* boson in the *t*-channel (*tZq*). The process, observed in 2019, is interesting because it can give insights on the coupling between the *top* quark and the *Z* boson. Moreover, this process is an important background to the *tHq* process, which allows to probe the *tH* Yukawa coupling, and in particular it is sensitive to its sign.

This thesis aims at improving the inclusive *tZq* cross section measurement performed by the ATLAS experiment, using the full Run2 dataset, in which a 15% uncertainty on the cross section was achieved, with $\sigma_{tZq}^{\text{Observed}} = 97^{+14}_{-13} \text{ fb} = 97^{+13}_{-12}(\text{stat}) \pm 7(\text{syst}) \text{ fb}$.

In Chapter 1 a brief introduction on the Standard Model is presented, whereas Chapter 2 focuses on the Top quark. The LHC and the ATLAS detector are described in Chapter 3, and the analysis setup, in which samples, object reconstruction and event selection are reported, is presented in Chapter 4. Chapter 5 describes the data-driven estimation of some of the dominant backgrounds, whereas Chapter 6 presents an AI-based analysis aimed at improving the separation between signal and the background sources. In Chapter 7 the binned-profile Likelihood fits to measure the cross section are presented, and finally, in Chapter 8, ATLAS' first measurement of the ratio between the cross sections of *top* and *antitop* quark production in association with a *Z* is reported.

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Chapter 1

The Standard Model

The Standard Model (SM) is a quantum-relativistic theory for the elementary particles. It describes three of the four fundamental interactions, which are the electromagnetic, the strong nuclear, and the weak nuclear. The fourth, gravity, is not yet included in the Standard Model.

1.1 The structure of the Standard Model

The Standard Model is a gauge theory built on a $SU(3) \times SU(2)_L \times U(1)_Y$ symmetry. The $U(1)_Y$ symmetry refers to *hypercharge*. $SU(2)_L$ is the *weak isospin* symmetry, acting only on left-handed fermions. $SU(3)$ is the *colour charge* symmetry of the strong interaction. In the SM for high energies the weak nuclear interaction and the electromagnetic interaction are unified into the electroweak interaction, with a $SU(2)_L \times U(1)_Y$ symmetry. Due to the Higgs Mechanism, the electroweak symmetry is spontaneously broken. Therefore, three gauge fields W^+ , W^- and Z acquire mass, whereas the A field, describing the photon, remains massless.

The elementary particles described by the SM are represented in Figure 1.1. There are two types of particles, *fermions* and *bosons*. Fermions have half-integer spin (in the SM $S = 1/2$) and obey Fermi-Dirac statistics, so two identical fermions have an anti-symmetric wavefunction. Contrasting this, bosons have integer spin (in the SM $S = 0, 1$) and obey Bose-Einstein statistics, resulting in two identical bosons having a symmetric wavefunction.

Fermions in the SM appear as leptons and quarks. Leptons are grouped into three families, each containing a negatively (-1, in unity of the electric charge) charged massive particle and its corresponding neutral neutrino. The three families are the electron family (e and ν_e), the muon family (μ and ν_μ), and the tau family (τ and ν_τ). In each family the left-handed chiral component is a weak isospin doublet differing only in their masses [1], and the right-handed component is a weak isospin singlet. Quarks are also grouped in three families according to mass eigenstates. The three families are the up family (up, down), the charm family (charm, strange) and the top family (top, bottom). They have

fractional charge ($2/3$ for u, c and t and $-1/3$ for d, s and b) and different values of masses [1], with the up quark being the lightest ($m_u \simeq 2$ MeV) and the top quark being the heaviest ($m_t = 173$ GeV). All the quarks have baryon number $B = 1/3$, meaning it takes three quarks to form a baryon and a quark-antiquark pair to form a meson. Differing from baryons, leptons have baryon number $B = 0$ and lepton number $L = 1$. Each lepton family also has a flavour number, 1 for the particle and -1 for the antiparticle, which is conserved in all interactions except for neutrino oscillations. Each fermion in the SM has a corresponding anti-fermion with the same mass but opposite quantum numbers. In order for the SM theory to be gauge-invariant, the SM Lagrangian has to be built with massless fermions. This is needed because a fermion mass term such as the electron, in the Lagrangian would appear as $m\bar{e}_R\psi_L$, with e_R being a isospin singlet and ψ_L being the weak isospin doublet. This term would break the gauge invariance because the singlet and the doublet transform differently under the $SU(2)_L \times U(1)_Y$ symmetry. Therefore, the SM Lagrangian considers massless fermion; their mass is added separately via the Higgs mechanism [2].

The bosons in the SM are the interaction carriers and the Higgs boson. The force carriers are the gauge vector bosons with spin $S = 1$, whereas the Higgs boson is the only scalar in the SM, having spin $S = 0$. We can categorize the force carriers by which interaction they carry: the photon is responsible for the electromagnetic interaction, acting only on charged particles, the gluon mediates the strong interaction between coloured particles, and the W and Z bosons are the carriers of the weak interaction between particles with weak isospin. A boson mass term for the photon in the Lagrangian would be $\frac{m^2}{2}A_\mu A^\mu$, a term which is not gauge-invariant under the $U(1)$ symmetry. The mass term is not gauge-invariant even for massive gauge bosons, such as the W and Z . Therefore, similar to the fermions, we have to build a massless Lagrangian for the free fields in order to preserve gauge invariance, and will add the masses through the interaction between the gauge bosons and the Higgs boson. The W and Z bosons have mass [1] because they interact with the Higgs Boson, since the vacuum has hypercharge and weak isospin, whereas the photon and the gluon are massless because the vacuum is colourless and neutrally charged. The Z boson has a mass $m_Z = 90.2$ GeV [1] and a neutral electrical charge, and is therefore responsible for the neutral weak current. The W boson is responsible for the charged weak current, therefore it exists in two different charged states ($W^{\pm 1}$). Its mass is $m_W = 80.4$ GeV [1].

Finally, the Higgs boson is the scalar responsible for the masses of the particles through the mechanism of spontaneous breaking of the symmetry. The $SU(3) \times SU(2)_L \times U(1)_Y$ symmetry is preserved, whereas the vacuum loses its symmetry due to the Higgs mechanism. The Higgs boson is the newest member of the SM, discovered only in 2012 at LHC independently by the ATLAS experiment [3] and the CMS experiment [4], almost 50 years after it was theorized [2]. The Higgs boson is the heaviest boson in the SM, with a mass of $m_H = 125$ GeV [1].

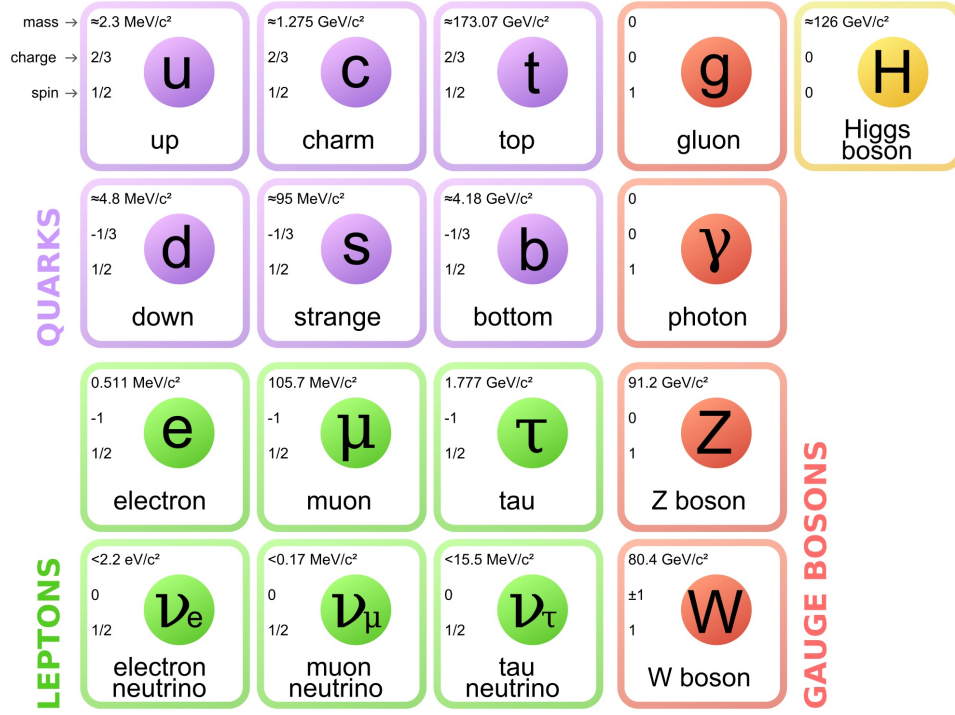


Figure 1.1: Scheme of the elementary particles described by the SM of particle physics with information regarding the mass, the charge and the spin of each particle.

1.2 Fundamental interactions

1.2.1 Quantum Electrodynamics

Quantum Electrodynamics (QED) is the quantum field theory describing the interaction between charged particles built on a local $U(1)$ gauge symmetry. All the quarks, the charged leptons, and the W boson interact with the photon. Out of the three fundamental interactions, it is the only one having a classical theory, finalised by James Maxwell [5]. It is described by Maxwell equation, which can be written in a covariant way as in Equation (1.2.1), where J^μ and $F^{\mu\nu}$ refer to the current four-vector and to the field tensor, respectively.

$$\partial_\nu F^{\nu\mu} = J^\mu \quad (1.2.1)$$

This interaction is mediated by the photon, and therefore has infinite range¹, since the photon is massless. Because the photon also has neutral charge, QED is an abelian gauge theory and therefore photon-photon interactions are not possible at Leading Order (LO). The charge of the interaction is the electric charge, and the coupling constant is α , equal to $\frac{e^2}{4\pi} \simeq 1/137$, defined as the fine structure constant. QED doesn't distinguish between left and right fermions, and is therefore invariant under parity.

¹The range of an interaction can be calculated as $R = \frac{1}{m}$ in natural units

1.2.2 Electroweak interaction

The electroweak interaction is the interaction that mixes QED and weak neutral interaction and it is built on a local $SU(2)_L \times U(1)_Y$ gauge symmetry. There are four mathematical vector bosons which mediate this interaction, called W_1, W_2, W_3 and B . A particular linear combination² of these four bosons gives the real physical bosons, which are $W^\pm$, Z and A , representing the two charge W boson, the Z boson and the photon A .

The A^μ field interacts electromagnetically, as described in the previous section, and is massless, because the eigenvalue of its interaction with the Higgs field is zero. The $W^\pm$ fields interact weakly only with left-handed particles. They represent the charged weak current, which is built on $SU(2)_L$ symmetry. Because of their interaction with the Higgs boson, they acquire mass, with $m_W = 80.4$ GeV [1], despite new measurements of this mass performed by both ATLAS [6] and CDF [7] show a disparity, with the latter hinting at potential beyond Standard Model physics.

Finally, the Z boson is the mediator of the weak neutral current. Analogous to the W boson, it is massive, and the heaviest vector boson in the Standard Model, with a mass $m_Z = 90.2$ GeV [1]. The Z boson interacts with both right- and left-handed fermions having weak neutral charge and isospin as in Equation (1.2.2), where g is the coupling constant of the weak interaction, and θ_W is the Weinberg mixing angle, with the two correlated as $e = g \sin \theta_W = g' \cos \theta_W$. We can see that the Z boson interacts with both the electro-magnetic ($\bar{f}\gamma^\mu f$) and the J_3 current ($T_3^f \bar{f}\gamma^\mu (1 - \gamma^5)f$).

$$Z_\mu \frac{g}{2 \cos \theta_W} \left(T_3^f \bar{f}\gamma^\mu (1 - \gamma^5)f + 2Q_f \sin^2 \theta_W \bar{f}\gamma^\mu f \right) \quad (1.2.2)$$

The coupling is not left-right symmetric, as it is different for the two chiral components. The left-handed component of the fermions, being an isospin doublet, interacts with both J_3^μ and with the electromagnetic current. On the other hand, the right-handed component, being an isospin singlet, does not interact with J_3^μ . Therefore, the interaction between the Z boson and right-handed fermions is only electromagnetically, with a factor $g \sin^2 \theta_W / \cos \theta_W$. The Z boson interacts only between fermions of the same type, and therefore Flavour-Changing-Neutral-Currents (FCNC) are not allowed at tree-level. Thus, an electron-muon- Z vertex is prohibited, and only $e\bar{e}Z$ or $\mu\bar{\mu}Z$ vertices are permitted.

Lepton mass eigenstates are the same as flavour eigenstates. Consequently, interactions between leptons mediated by the W boson are possible only between leptons belonging to the same isospin doublet, i.e. electron with electronic neutrino, and so on. For quarks it is more complicated than that, since mass eigenstates differ from flavour eigenstates. Therefore, the charged weak interactions for quarks are possible also outside the family. This happens because the flavour eigenstates are a linear combination of the mass eigenstates, with the Cabibbo-Kobayashi-Maskawa (CKM [8]) matrix being the mixing

² $W^\pm = 1/\sqrt{2} (W_1 \pm iW_2)$, $Z = W_3 \cos \theta_W - B \sin \theta_W$ and $A = W_3 \sin \theta_W + B \cos \theta_W$

matrix between the two different sets of eigenstates, as described in Equation (1.2.3).

$$\begin{pmatrix} d' \\ s' \\ b' \end{pmatrix} = \begin{pmatrix} V_{ud} & V_{us} & V_{ub} \\ V_{cd} & V_{cs} & V_{cb} \\ V_{td} & V_{ts} & V_{tb} \end{pmatrix} \begin{pmatrix} d \\ s \\ b \end{pmatrix} \quad (1.2.3)$$

The CKM matrix is a unitary matrix, with the diagonal elements being the largest ($V_{ud} \simeq 0.97$, $V_{cs} \simeq 0.97$, $V_{tb} \simeq 0.99$. These values are taken from Wolfenstein's parametrization of the CKM matrix [9]). That is because, even though it is true that the up quark interacts with d' and not d , the probability of interacting with d is larger than the probability (which is proportional to $|V_{ij}|^2$) of interacting with, for example, s ($V_{us} \simeq 0.23$). Because V_{tb} is almost equal to 1, the probability of a *top* quark to interact with any quark different from the *bottom* quark is null.

The fermions in the electroweak Lagrangian appear as left-handed spinors in doublets and, if they have mass, right-handed singlets, as can be seen in Equation (1.2.4). Neutrinos are considered massless, and therefore they lack a right-handed singlet term.

$$\begin{pmatrix} \nu_e \\ e \end{pmatrix}_L, \begin{pmatrix} \nu_\mu \\ \mu \end{pmatrix}_L, \begin{pmatrix} \nu_\tau \\ \tau \end{pmatrix}_L, \begin{pmatrix} u \\ d' \end{pmatrix}_L, \begin{pmatrix} c \\ s' \end{pmatrix}_L, \begin{pmatrix} t \\ b' \end{pmatrix}_L; e_R, \mu_R, \tau_R, u_R, c_R, t_R, d'_R, s'_R, b'_R \quad (1.2.4)$$

1.2.3 Quantum Chromodynamics

Quantum Chromodynamics (QCD) is the quantum theory that describes the strong nuclear interaction. It is the interaction that acts only on quarks, and its carrier is the gluon, a massless neutral vector boson having colour charge. The colour charge has the same purpose as the electric charge does for the electromagnetic interaction, in that the strong interaction is the interaction between particles having colour charge. There are three different colour states (red, green and blue), so the symmetry is $SU(3)$, generated by the eight Gell-Mann matrices. This means that every quark in the Standard Model can appear in three different states. The non elementary particles, like baryons and mesons, are colourless, because the total antisymmetric combination $\frac{1}{\sqrt{6}}(rgb + brg + gbr - grb - rbg - bgr)$ of colours generates “white”, a colour singlet.

There are eight different gluons (Equation (1.2.5)), each having a colour charge.

$$r\bar{g}, g\bar{r}, r\bar{b}, b\bar{r}, g\bar{b}, b\bar{g}, 1/\sqrt{2}(r\bar{r} - g\bar{g}), 1/2(r\bar{r} + g\bar{g} - 2b\bar{b}) \quad (1.2.5)$$

The main difference between the colour charge and the electric charge is that the gluon has colour, whereas the photon doesn't have electric charge. This means that LO interactions between gluons are possible, because $SU(3)$ is a non-abelian group, while interactions between photons are suppressed in the first order of QED theory, being $U(1)$ abelian. QCD also differs from QED and EW because the strong coupling decreases at higher energies, as opposed to QED's increasing coupling. Therefore, a perturbative approach on QCD

can only be applied at high energies, whereas for energies below the GeV scale other approaches must be considered, such as Effective Field Theory or Lattice QCD.

1.3 The Lagrangian of the Standard Model

The equation describing the motion of a spinor is Dirac equation (Equation (1.3.1))

$$(i\gamma^\mu \partial_\mu - m) \psi = 0 \quad (1.3.1)$$

Where ψ is a four-component spinor, and the gammas are Dirac matrices³ [10].

The free Dirac Lagrangian is represented in Equation (1.3.2), where a mass term is not present, as aforementioned.

$$L = i\bar{\psi}\gamma^\mu \partial_\mu \psi \quad (1.3.2)$$

The other terms in the Lagrangian are the interactions with the fields, interactions which are generated once local gauge invariance is required, and the free field. Gluons, W bosons, and B also have self-interacting terms, because $SU(3)$ and $SU(2)_L \times U(1)_Y$ are not abelian groups.

The complete SM Lagrangian can be written as in Equation (1.3.3)

$$\begin{aligned} \mathcal{L} = & \bar{R}_\ell i\gamma^\mu \left(\partial_\mu + i\frac{g'}{2} B_\mu Y \right) R_\ell + \bar{L}_\ell i\gamma^\mu \left(\partial_\mu + i\frac{g'}{2} B_\mu Y + i\frac{g}{2} \vec{\sigma} \cdot \vec{W}_\mu \right) L_\ell + \\ & + \bar{R}_q i\gamma^\mu \left(\partial_\mu + i\frac{g'}{2} B_\mu Y + i\frac{g_s}{2} G_\mu^k \lambda_k \right) R_q + \\ & + \bar{L}_q i\gamma^\mu \left(\partial_\mu + i\frac{g'}{2} B_\mu Y + i\frac{g}{2} \vec{\sigma} \cdot \vec{W}_\mu + i\frac{g_s}{2} G_\mu^k \lambda_k \right) L_q + \\ & - \frac{1}{4} W_{\ell\mu\nu} W^{\ell\mu\nu} - \frac{1}{4} B_{\mu\nu} B^{\mu\nu} - \frac{1}{4} G_{k\mu\nu} G^{k\mu\nu} \end{aligned} \quad (1.3.3)$$

R_ℓ refers to right-handed singlets for massive leptons (here neutrinos are considered massless), which interacts only with the hypercharge current $B_\mu Y$ with a coupling constant g' . L_ℓ is the lepton left-handed doublet spinor, which, in addition to interacting with the hypercharge current, same as the right-handed ones, also interacts with the weak isospin current ($\vec{\sigma}$ are the three Pauli matrices and $\vec{W}_\mu$ are the three W boson fields) with a coupling constant g . For the quarks there are two different terms as well. The former is the right-handed singlet term for the six quarks in their mass eigenstates (so $u_R, d_R, c_R, s_R, t_R, b_R$). They don't interact with the weak isospin current, as they are isospin singlets, and therefore interact only with the colour current (λ_k are the eight Gell-Mann matrices, $k = 1, \dots, 8$; G_μ^k is the gluon field) with a coupling constant g_s . The remaining quark terms refer to the left-handed doublets of quarks, which interacts with

3

$$\gamma^0 = \begin{pmatrix} \mathbb{I}_{2 \times 2} & 0_{2 \times 2} \\ 0_{2 \times 2} & -\mathbb{I}_{2 \times 2} \end{pmatrix}, \quad \gamma^i = \begin{pmatrix} 0_{2 \times 2} & \sigma_i \\ -\sigma_i & 0_{2 \times 2} \end{pmatrix}$$

all the three currents. Every term has also a free massless Dirac Lagrangian.

Finally there are three free fields, given by $B_{\mu\nu}$, $W_{\ell\mu\nu}$ and $G_{k\mu\nu}$. They are defined as linear combinations of space-time derivatives of B_μ , $W_{\ell\mu}$ and $G_{k\mu}$, describing the free propagation, and for $W_{\ell\mu\nu}$ and $G_{k\mu\nu}$ they also contain self-interacting terms.

1.4 The Higgs Mechanism

There is still one particle in the SM that did not appear in the Lagrangian written in Equation (1.3.3), the Higgs boson. The Higgs boson is the scalar term, responsible for the masses of the fermions and the masses of the W and Z bosons, by means of the spontaneous symmetry breaking. The Higgs boson doesn't satisfy Dirac equation (Equation (1.3.1)), which only works for fermions, but it satisfy Klein Gordon equation (Equation (1.4.1)). The SM Higgs boson appears as doublet scalar complex Φ , whose local gauge invariant Lagrangian is written in Equation (1.4.2), where $D_\mu = \partial_\mu + ig/2 W_\mu^j \sigma^j + ig'/2 B_\mu$.

$$\left(\partial_\mu \partial^\mu + m^2\right) \Phi = 0 \quad (1.4.1)$$

$$\mathcal{L} = (D_\mu \Phi)^\dagger (D^\mu \Phi) - \frac{1}{2} \mu^2 \Phi^\dagger \Phi - \lambda (\Phi^\dagger \Phi)^2 \quad (1.4.2)$$

A simpler, 2-D visualisation of the Higgs potential can be seen in Figure 1.2, where the one-dimensional potential is simply $-\mu^2 \phi^2 + \lambda \phi^4$. If $-\mu^2 > 0$, the potential has two different minima, at $\phi = \pm \frac{\mu}{\lambda}$. Thus, spontaneous symmetry breaking occurs. This refers to a situation in which the potential has multiple minima, and by choosing one of the minima we lose the symmetry that the potential holds. It differs from the explicit symmetry breaking in that the Lagrangian is still invariant under the group transformation, but the ground state is not.

The spontaneous breaking can be observed by explicitly expanding the potential around the minima, but I am not going to make those calculations here. The important thing is that once we select a minima, meaning that we expand around one of the minima, we obtain a term of the type $-\mu^2 \sigma^2$, where σ is a scalar field. Therefore, the scalar Higgs field gains mass through spontaneous symmetry breaking. The spontaneous symmetry breaking that happens in the Standard Model is more complicated than what I have just explained, because the symmetry which breaks is not $U(1)$, as it was in the example before, but it is $SU(2)_L \times U(1)_Y$, therefore giving birth to the Electroweak Spontaneous Symmetry Breaking (EWSB). In EWSB we consider the Lagrangian in Equation (1.4.2), of which a plot can be seen in Figure 1.3. This potential has infinite degenerate minima, all located at the bottom of the well, of the type described in Equation (1.4.3), where we have defined $v \doteq \sqrt{\frac{-\mu^2}{2\lambda}}$, also called VEV, vacuum expectation value ($v = 246.21965 \pm 0.00006$ GeV).

$$\Phi_0 = \begin{pmatrix} 0 \\ \sqrt{\frac{-\mu^2}{2\lambda}} \end{pmatrix} e^{i\theta} \doteq \begin{pmatrix} 0 \\ v \end{pmatrix} e^{i\theta} \quad (1.4.3)$$

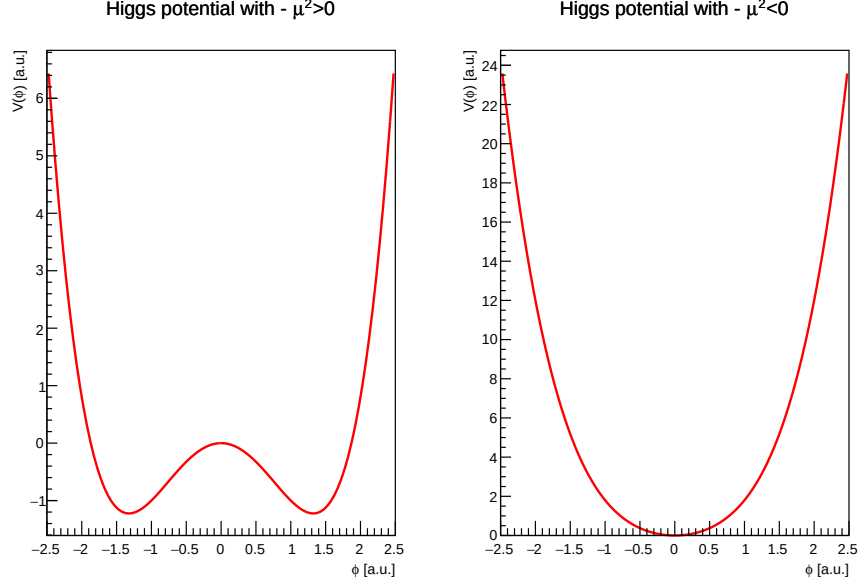
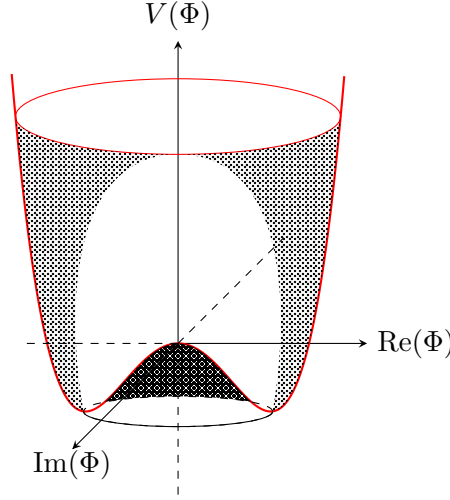


Figure 1.2: Higgs potential for $-\mu^2 > 0$ and for $-\mu^2 < 0$. We can see how the spontaneous symmetry breaking occurs only for the first scenario

If we expand around the minima in Equation (1.4.3) as $\Phi^\dagger = \frac{1}{\sqrt{2}}(0, v + \sigma)$, we obtain a Lagrangian which contains a term $1/2 \partial_\mu \sigma \partial^\mu \sigma - 1/2 (-2\mu^2) \sigma^2$, which is the Klein-Gordon Lagrangian for a massive scalar field σ , whose mass is $m_\sigma^2 = -2\mu^2$. This is the mass term of the Higgs boson, which gains mass thanks to the EWSB. But the Higgs boson is not the only particle that acquires mass due to the EWSB. Additional terms that appear in the Lagrangian are $1/4 g^2 v^2 W_\mu^+ W^{\mu-}$, which is the mass term for the W boson, and $1/8 v^2 \cdot (g^2 + g'^2) Z_\mu Z^\mu$, which refers to the massive term for the Z boson. Therefore, as a consequence of the EWSB, the Higgs, the W and the Z bosons all acquire mass, with $m_H^2 = -2\mu^2$, $m_W^2 = \frac{g^2 v^2}{4}$ and $m_Z^2 = \frac{v^2}{4}(g^2 + g'^2)$. Moreover, additional terms in the Lagrangian include triple and quadruple Higgs coupling, proportional to λv and λ respectively, VVH , and $VVHH$ couplings, where V indicates both W and Z boson, proportional to the vector boson masses squared ($\alpha = \frac{2m_V^2}{v}$). The only boson which does not interact with the Higgs boson is the photon, because in the end there remains a residual $U(1)$ symmetry. Consequently, the photon remains massless. Alongside the photon, the gluon stays massless as well, because the symmetry breaking is $SU(2)_L \times U(1)_Y$ and not $SU(3)$.

Instead, fermions behave differently. As discussed earlier, a mass term for fermions would break local gauge invariance. Therefore, the mass terms are introduced “by hand” in the Lagrangian, as in Equation (1.4.4), where Q_L refers to the left-handed doublet spinor, d_R and u_R refers to the right-handed singlets of fermions of type down and up respectively⁴, $\tilde{\Phi}$ refers to the charge conjugate of Φ and Y is called Yukawa coupling

⁴Here this discussion is carried out using u and d , as if I were referring to quarks up and down, but the


 Figure 1.3: The 3D Higgs potential with $-\mu^2 > 0$

constant.

$$\mathcal{L} = -Y_d (\bar{Q}_L d_R \Phi + h.c.) - Y_u (\bar{Q}_L u_R \tilde{\Phi} + h.c.) \quad (1.4.4)$$

Using the same expansion around the minima we used for the EWSB earlier, we get a Lagrangian with terms like $-Y_u/\sqrt{2} \bar{u}_L u_R (v + \sigma) + h.c.$, plus the same term for d . We can note a term proportional to $Y_u \bar{u}_L u_R$, which is the mass term with $m_u = \frac{v Y_u}{\sqrt{2}}$, and a term proportional to $Y_u \bar{u}_L \sigma u_R$, which refers to the $f\bar{f}H$ interaction. This fermion-Higgs interaction is proportional to Y_f , therefore making it proportional to the mass of the fermions (because $Y_f \sim m_f$).

In the end, we have:

- Two massive charged vector bosons ($W^\pm$)
- A massless vector boson (γ)
- A massive neutral vector boson (Z)
- A massive neutral scalar boson (the Higgs boson, H)
- 6 massive charged quarks
- 3 massive charged leptons
- 3 massless neutral neutrinos

Because of the coupling constant for fermions being proportional to the mass of the fermion, the *top* quark, being the heaviest particle in the SM, is the particle which interacts the most with Higgs boson. In Figure 1.4 a scheme of the interactions between the

discussion holds the same for all other quarks and for the leptons, where u and d can be replaced with ν_ℓ and ℓ respectively.

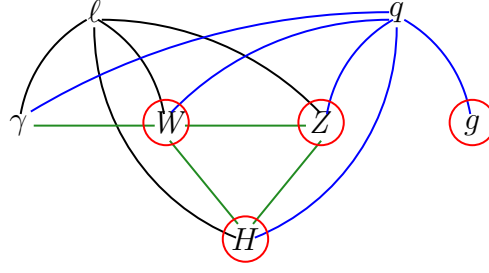


Figure 1.4: A scheme representing the interactions between the particles in the Standard Model. The black lines represent the interactions for the leptons, the blue lines represent the interactions for the quarks, the green lines represent the interactions between the bosons and the red circles represent the self-interactions.

fermions and the vector bosons with the Higgs boson is represented, whereas Figure 1.5 represents all the possible tree-level couplings in the SM.

1.5 The cross section

The purpose of my thesis is to measure the cross section of the tZq process. Therefore, in this section I will briefly explain what the cross section is and how the proton-proton cross section is calculated at hadron colliders.

1.5.1 Fermi's Golden Rule

The cross section is a measure of a surface, and its unit of measure is the barn (b), with $1\text{b} = 10^{-24}\text{cm}^2$. In classical scattering experiment the cross section can be defined as the proportional constant between the interaction rate and the product of incident flux and number of targets, as seen in Equation (1.5.1). This definition allows for a simple visualisation of the cross section, which can be seen as the transverse area of the target which, if hit by an incident flux Φ , gives an interaction rate of dn/dt .

$$\frac{dn(\theta)}{dt} = N_T \Phi_0 \frac{d\sigma}{d\Omega} \quad (1.5.1)$$

In quantum mechanics, the differential cross section is defined as the proportional constant between the transition probability rate $\dot{P}$ and the incident particle flux Φ , as per Equation (1.5.2). $\dot{P}$ refers to the probability rate that a transition between an asymptotic initial state $|i\rangle$ and a final state $|f\rangle$ occurs.

$$d\sigma_{i \rightarrow f} = \frac{\dot{P}_{i \rightarrow f}}{\Phi_i} \quad (1.5.2)$$

The two equations are linked through Fermi's Golden Rule [11], which defines the transition probability as in Equation (1.5.3), where $V_{i,f}$ refers to the potential of the perturbation

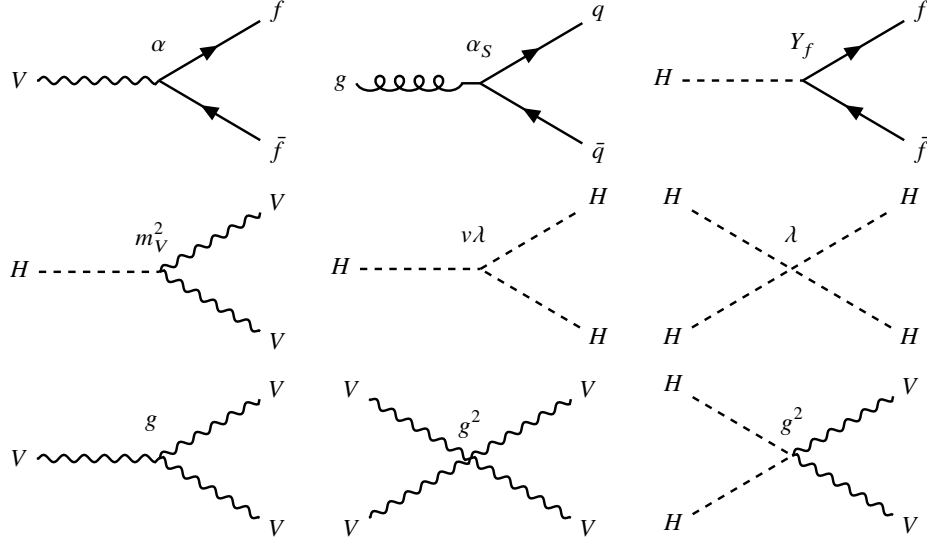


Figure 1.5: All the possible tree-level interactions in the SM. In the top row we have fermion-vector boson interaction, with the boson being either a Z , a γ or a W , and in the latter case we have f and $\bar{f}$. Then we have gluon splitting, only for quarks, and finally the Yukawa coupling $H - f\bar{f}$. In the middle we find Higgs couplings with two vector bosons and then a triple and quadruple Higgs coupling. Finally, we have triple and quadruple vector boson coupling and a $HHVV$ coupling.

Hamiltonian which allows for $|i\rangle \rightarrow |f\rangle$ transitions and $\rho(E_f)$ is the phase space density of final states.

$$\dot{P}_{i \rightarrow f} = \frac{2\pi}{\hbar} |\langle f | V_{f,i} | i \rangle|^2 \rho(E_f) \quad (1.5.3)$$

Therefore, discarding $\hbar$, we find that the differential cross section is defined as in Equation (1.5.4).

$$d\sigma_{i \rightarrow f} = \frac{2\pi}{\Phi_i} |\langle f | V_{f,i} | i \rangle|^2 \rho(E_f) \quad (1.5.4)$$

The detailed calculation will not be carried out in this thesis, and here I will present only the result for the differential cross section for a two-particles initial state in Equation (1.5.5), where $\mathcal{M}_{fi} \doteq \langle f | V_{f,i} | i \rangle$, $\delta^{(4)}$ refers to the 4-dimensional Dirac delta, P is the four-momentum, $\vec{p}$ is the tri-momentum and v_{rel} is the relative velocity between the two initial particles, $\vec{v}_{\text{rel}} = \frac{\vec{p}_2}{E_2} - \frac{\vec{p}_1}{E_1}$.

$$d\sigma_{i \rightarrow f} = (2\pi)^4 \delta^{(4)} \left(\sum_f P_f - \sum_i P_i \right) \frac{1}{4E_1 E_2 v_{\text{rel}}} \prod_f \frac{d^3 \vec{p}_f}{(2\pi)^3 2E_f} |\mathcal{M}_{fi}|^2 \quad (1.5.5)$$

Equation (1.5.5) refers to the differential cross section, that is, the cross section evaluated with respect to a certain variable, which can be the spherical angle, as is the case in fixed-target experiments, or a kinematic variable such as p_T . The inclusive cross section is the

integral over all the variables of the differential cross section (Equation (1.5.6)).

$$\sigma = \int d\sigma \quad (1.5.6)$$

1.5.2 Proton-proton deep inelastic scattering cross section

The proton p is a non-elementary fermion of spin $S = 1/2$, that is a particle made of other particles, in particularly quarks and gluons. It is a baryon with mass $m_P = 938$ MeV and positive unitary charge. Before the parton model [12], the proton was considered to be made of three quarks, precisely u, u, d . This model explained the baryon number ($B = 1$, because each quark has $B = 1/3$) and the charge ($Q = 1 = 2/3 + 2/3 - 1/3$). What wasn't yet explained was Bjorken's scaling phenomena in the cross section for electron-proton scattering.

Bjorken's scaling refers to observations made by the SLAC experiment [13] of a cross section which depends on only one variable, instead of two, as an inelastic scattering would demand. This phenomena was explained with the idea that at high energies the deep inelastic scattering between electron and proton behaves as an elastic scattering between electron and quarks, because the high energy of the electron allows it to probe the internal structure of the proton. Therefore, we cannot say that the proton is made by only three quarks. Instead, inside a proton there is a mixture of quarks, antiquarks, and gluons, each carrying a fraction of the total momentum of the proton. The internal structure of the proton is therefore dynamic, with quarks, antiquarks, and gluons having a certain probability of carrying a fraction of the proton momentum.

The Parton Distribution Functions (PDFs) [14] $f_a(x)$ are the functions which describe the probability for a parton a (be it a quark, anti-quark or a gluon) to carry a fraction x of the total momentum of the proton. Moreover, at SLAC it was observed that the total proton momentum fraction that interacted with the electrons was less than 0.5, therefore gluons, even if massless, carry more than half of the momentum of the proton⁵. Therefore, the deep inelastic cross section between electron and proton can be written as in Equation (1.5.7), where $\sigma_{\ell p \rightarrow \ell X}$ refers to the Deep Inelastic Scattering (DIS) cross section happening at momentum p , $\hat{\sigma}_{\ell i \rightarrow \ell X'}$ refers to the hard scattering between electrons and partons i (only quarks or anti-quarks), happening at momentum $p' = xp$, x is Bjorken's variable describing the fraction of proton momentum carried by the parton and $f_{p \rightarrow i}(x)$ is the PDF, which states the probability for a proton of fragmenting into a parton i . We then integrate over all the possible values the proton momentum fraction can hold, which is from 0 to 1, and we sum over all possible partons. Finally, the correction $O\left(\frac{\lambda_{QCD}}{Q}\right)$

⁵Gluon contribution to the proton momentum was not seen at SLAC because electrons do not interact with gluons.

accounts for non-perturbative contributes to the cross section.

$$\sigma_{\ell p \rightarrow \ell X}(p) \sim \sum_{i=q, \bar{q}, g} \int_0^1 dx f_{p \rightarrow i}(x) \hat{\sigma}_{\ell i \rightarrow \ell X'}(xp) + O\left(\frac{\lambda_{QCD}}{Q}\right) \quad (1.5.7)$$

Hadrons Factorisation theorem [15] ensure that the processes of fragmentation and hard scattering can be factorised, since they occur at different energies (and therefore, at different time scales) and are thus Markovian.

The Parton Distribution Functions, similar to the QFT couplings, are parameters of the theory, and therefore have to be renormalized in order for the theory to hold. Therefore, the so-called “bare” PDFs cannot be measured, but what can be measured is the “physical” PDF which absorbs the divergencies. Consequently, PDFs do not depend on x alone, but they also have a dependence from the factorisation scale μ_F , which is the energy scale chosen to energetically separate fragmentation from hard cross section. The universal formula for DIS cross section is defined in Equation (1.5.8). Q^2 refers to the hard scale of the process, $\alpha_S(Q^2)$ is the renormalized strong coupling and μ_F is the factorisation scale.

$$\sigma_{\ell p \rightarrow \ell X}(P, Q^2) = \sum_{i=q, \bar{q}, g} \int_0^1 dx \hat{\sigma}_{\ell i \rightarrow \ell X'}(xp; \alpha_S(Q^2), \mu_F^2) f_{p \rightarrow i}(x, \mu_F^2) \quad (1.5.8)$$

PDFs were first defined as a function of only one variable, x , the fraction of momentum of the proton carried by the parton, and we have then seen that there’s also a dependence from the factorisation scale μ_F (even though the latter is only a residual dependence⁶). However, PDFs are actually scale-dependent, that is, they have a non-trivial dependence from the energy at which the process is happening. Therefore, $f_q = f_q(x, s)$. This is caused by the scaling violation, which occurs because at even higher energies, the electron not only sees the internal structure of the proton, but it can also see Higher Order virtual correction, in which partons emit QCD radiation and therefore split. The scaling violation is represented in Figure 1.6, in which we can see that at higher energies there is a lower probability for partons to carry a large fraction of the proton’s momentum. Scaling violation is described by the DGLAP (Dokshitzer, Gribov, Lipatov, Altarelli, Parisi) equation (Equation (1.5.9)) [16–18], in which we see how the PDFs $f(x, Q^2)$ change depending on the splitting probability function $P(\alpha(Q^2), z)$, which is the function that describes the probability of a parton to split into another parton with a fraction z of the parton’s momentum.

$$\frac{df(x, Q^2)}{d(\log Q^2)} = \int_0^1 \frac{dz}{z} P(\alpha(Q^2), z) f\left(\frac{x}{z}, Q^2\right) \quad (1.5.9)$$

⁶The μ_F dependence is said to be a higher-order dependence because you can always change the factorisation scale redefining it, and the real dependence from μ_F would be at the following order.

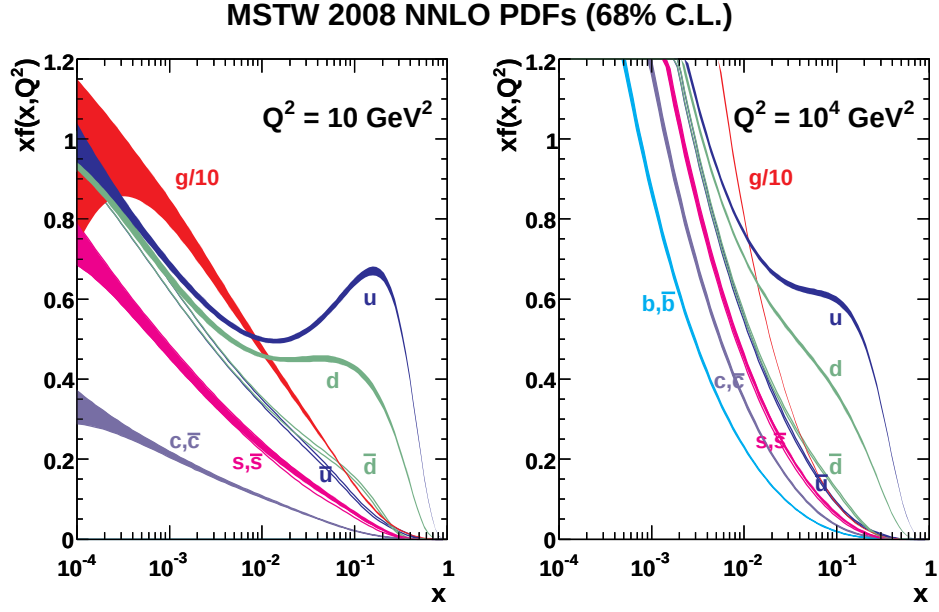


Figure 1.6: Parton distribution function of the proton, represented as a function of the transferred momentum Q^2 [19].

Finally, for proton-proton deep inelastic scattering ($pp \rightarrow F + x$, where F is the interested final state and x refers to all the rest) we must take into account all the consideration above, resulting in the followings:

- i)* Proton initial state fragmentation: Both protons enter the fragmentation phase, in which, since energies are really high, splitting is also accounted. One parton gets selected for each proton to participate in the hard scattering, carrying a fraction x_i of its proton momentum
- ii)* Initial state hadronization: Splitting and fragmentation generate hadron shower, which is the process in which the radiated partons, due to QCD confinement, generate bound states of hadrons
- iii)* Hard cross section: The selected partons from fragmentation interact with a hard cross section $\hat{\sigma}(x_1 p_1, x_2 p_2)$, where p_i is the energy of the proton i and x_i refers to the fraction of energy carried by the parton i
- iv)* Final state hadronization: When considering higher order corrections to the hard scattering, we are also considering final state radiation. Therefore, we must also take into account the hadron shower generated by the final state radiation, which generates additional hadrons

Therefore, the proton-proton deep inelastic cross section can be parametrized as in Equation (1.5.10), and a visualisation of the process can be found in Figure 1.7:

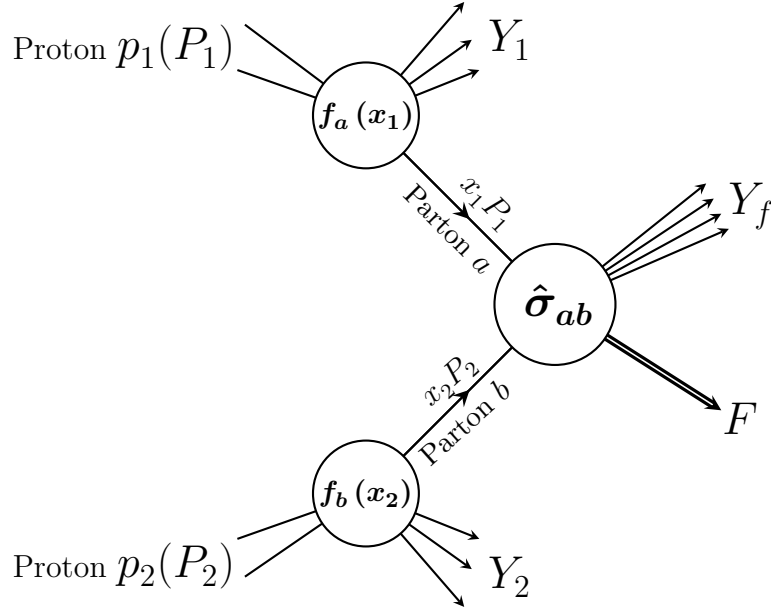


Figure 1.7: Representation of the proton-proton cross section, in which we can see the factorisation. First we have the splitting given by $f_i(x_j)$ ($i = a, b$, $j = 1, 2$), which selects a parton i with a fraction x_j of the proton momentum. The two partons then collide with a hard cross section $\hat{\sigma}_{ab}$, which generates our final state of interest F . Y_1 , Y_2 and Y_f refer to initial and final state corrections, and together they make up for the underlying event $X = Y_1 + Y_2 + Y_f$

$$\sigma(P_1, P_2; Q^2) = \sum_{a,b=q,\bar{q},g} \int_0^1 dx_1 dx_2 f_{a/p_1}(x_1, \mu_F^2) f_{b/p_2}(x_2, \mu_F^2) \hat{\sigma}_{ab}(x_1 P_1, x_2 P_2; \alpha_S(\mu_F^2), \mu_F^2, \mu_R^2, Q^2) \quad (1.5.10)$$

1.6 Beyond the Standard Model

The Standard Model is a theory that successfully describes the particle physics processes, with its predictions being confirmed with staggering precision in different experiments all over the world. However, there are still some observations that the Standard Model does not explain:

Dark Matter

From cosmological observations it is known that only 4% of the matter in the Universe is baryonic. The remaining 96% is made of what we call Dark Energy and Dark Matter (27%). Despite baryonic matter being explained in the Standard Model, Dark Matter is

not, and neither are the interactions between Dark and baryonic Matter. There are many candidates for Dark Matter, with the most promising being the WIMPs (Weakly interacting massive particles), particles that interact gravitationally but not electromagnetically. Many experiments are now active in search for the existence of Dark Matter, but so far there is no clear consensus about the observation of WIMPs.

Neutrino oscillations

Neutrinos are considered massless in the SM, therefore justifying the non-presence of a singlet right-handed component in the Lagrangian. Nevertheless, observations on solar neutrinos have proved the existence of neutrino oscillations [20]. Yet, in order to oscillate, the neutrino must be a massive particle. An additional issue caused by the neutrino oscillation is the violation of leptonic flavour, because if a ν_e oscillates into a ν_μ , the electronic number and the muonic number are not conserved, which is not allowed by the SM.

Gravitational interaction

The gravitational interaction is not yet included in the Standard Model. It has been theorized that, in case it were possible to have a quantum theory for gravity, the interaction carrier of the field would be the graviton, a boson of spin $S = 2$, which has not yet been discovered.

SUSY

Beyond Standard Model (BSM) theories nowadays include Supersymmetry (SUSY), a theory that would preserve the $SU(3) \times U(1) \times SU(2)$ symmetry, but, despite many searches being carried out over the past years, there are still no experimental evidences sustaining this theory.

Chapter 2

Top Quark Physics

The *top* quark is the latest fermion added to the SM. It was theorized in the 1980s to complete the weak isospin doublet with the *bottom* quark, and it was discovered only in 1995 by both D0 and CDF collaborations at the Fermilab collider [21, 22]. It is the heaviest particle in the SM, having a mass close to the electroweak symmetry breaking scale, almost 1.5 times heavier than the Higgs Boson. Therefore, the *top* Yukawa coupling is close to unity, precisely $Y_t \simeq 0.99^7$. Moreover, being heavier than the Z and W bosons, the *top* quark can decay into a real vector boson, instead of a virtual one, as it happens for the other fermions. Therefore, the *top* quark is the only quark which decays before hadronisation, thus not having bound states.

2.1 Top quark properties and decay

The *top* quark is the heaviest particle in the Standard Model, having a mass of $m_t = 172.67 \text{ GeV} \pm 0.30 \text{ GeV}$ [1]. Its electric charge is $Q_t = 2/3$ in terms of the unity charge. It appears in the SM as the $I_3 = +1/2$ component of a left-handed isospin doublet, together with the *bottom* quark, and in a right-handed singlet t_R . Because of the CPT theorem [23], the *antitop* $\bar{t}$ has same mass, $I_3 = -1/2$, $Q = -2/3$ and same decay time.

As aforementioned, the *top* quark couples weakly only with the *bottom* quark, because the matrix elements V_{td} and V_{ts} (Equation (1.2.3)) are almost zero (precisely $|V_{td}|^2 \simeq 7.6 \times 10^{-5}$ and $|V_{ts}|^2 \simeq 1.7 \times 10^{-3}$ [9]), as opposed to $V_{tb} \sim 1$.

Consequently, the *top* quark decays as in Equation (2.1.1) with a branching fraction close to 1 [1], with the Feynman diagrams represented in Figure 2.1.

$$t \rightarrow W^+ b \tag{2.1.1}$$

Figure 2.1(a) shows the W^+ boson decaying leptonically into a charged anti-lepton (in order to preserve the electric charge) and a neutrino of the same lepton family (in order to preserve the lepton number), whereas Figure 2.1(b) shows the W^+ boson decaying

⁷ $Y_t = \frac{\sqrt{2}m_t}{v}$

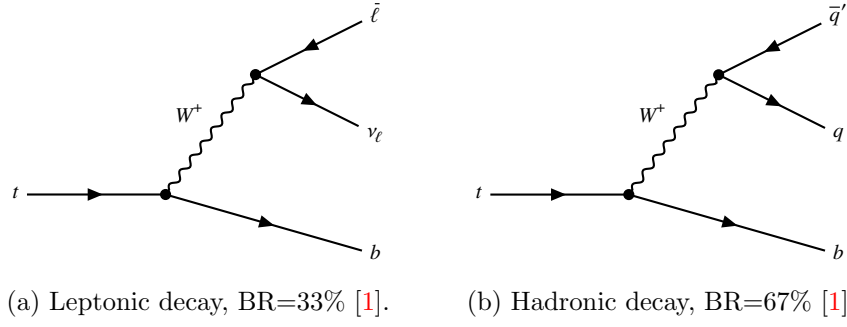


Figure 2.1: The two possible Feynman diagram of the *top* decay, based on the decay of the *W* boson

hadronically into a quark of “up” type (that is u, c) and an antiquark of “down” type (that is d', s', b' respectively).

The *top* quark decay is an electroweak process, and thus the quark flavour is not conserved, as opposed to strong processes. The *top* quark lifetime is $\tau_t \simeq 5 \times 10^{-25}$ s, lower than the average time it takes to form a hadron ($t \simeq 10^{-24}$ s), and therefore there are no *top* quark hadrons. An additional consequence of its small life time is that the resonance width $\Gamma = \hbar/\tau$ is only 0.8% of its mass, being $\Gamma_t = 1.42^{+0.19}_{-0.15}$ GeV [1].

2.2 Top quark production at the LHC

Because *top* quarks are so heavy and so unstable, they don’t appear in nature. Therefore, in order to be able to study them, they must be produced using very high energy hadron colliders, such as the Tevatron in the past and the Large Hadron Collider now. At these colliders, the possible *top* quark productions are *pair production*, *single top production* and *associated productions*.

2.2.1 Pair production

The dominant *top* quark production process is the $t\bar{t}$ pair production. $t\bar{t}$ refers to the strong production of a *top* and an *antitop* quarks. It requires very high energies, because to produce a $t\bar{t}$ pair there needs to be a centre of mass energy $\sqrt{s} \geq 2m_t \sim 345$ GeV. The $t\bar{t}$ pair production can occur in multiple ways, all through strong interaction, thus conserving the flavour. The LO processes are *gluon-gluon fusion* and *quark-antiquark annihilation*, of which Feynman diagram examples are in Figure 2.2.

At the Tevatron collider, the leading process was *quark-antiquark annihilation* (Figure 2.2(d)), with a branching fraction of 0.85. This was the dominant production method because the Fermilab accelerator collided protons and antiprotons. Therefore, it was much likely to find a quark and an antiquark that could annihilate into a gluon, which then split in $t\bar{t}$ pair. For this process to occur, the invariant mass of the $q \bar{q}$ system $m_{q\bar{q}}$ needed to be higher than two times the *top* mass, which is why the process was observed only at

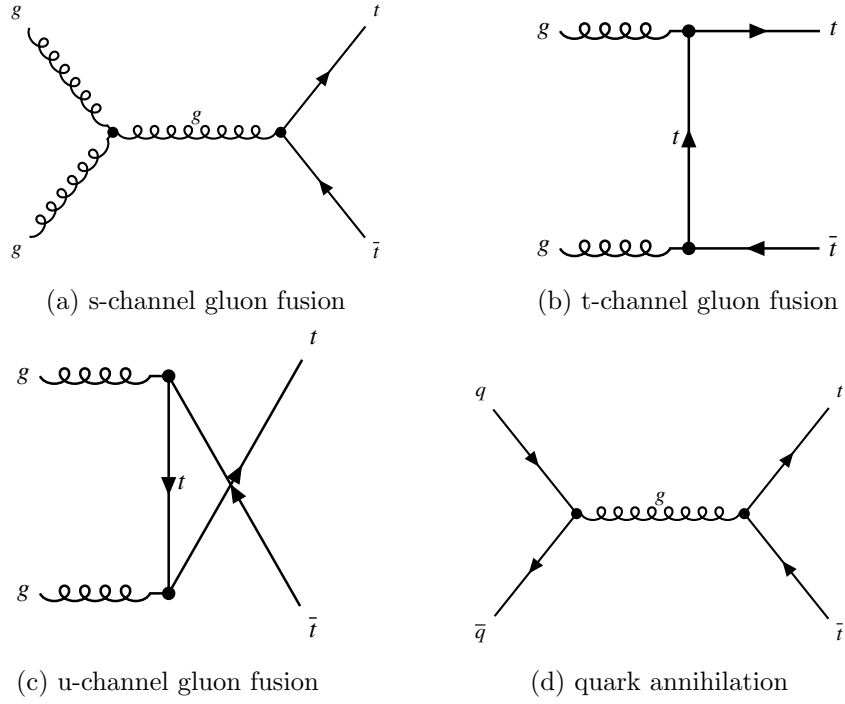


Figure 2.2: The four different LO Feynman diagrams for strong pair production of $t\bar{t}$. The two top diagrams refer to gluon fusion, the first with the s-channel exchange of a gluon, which then splits in $t\bar{t}$, whereas the second one has a *top* quark t-channel exchange. In the bottom we have the u-channel gluon fusion and finally quark annihilation.

Fermilab, thanks to its then-leading centre of mass energy of 1.96 TeV.

In contrast, at the Large Hadron Collider top quark pairs are produced mostly by *gluon-gluon fusion*. This process can occur both with the s-channel exchange of a gluon or with the exchange of a *top* quark in either t- or u- channel. Because the LHC is a proton-proton collider, it is less likely to find a $q\bar{q}$ pair which can annihilate into a gluon than it is to find two gluons, especially because, as aforementioned, gluons carry more than half of the proton's momentum. $t\bar{t}$ pairs are produced through *gluon-gluon fusion* roughly 90% of the times. Similarly to *quark-antiquark* annihilation, *gluon-gluon fusion* requires an invariant mass of the di-gluon system $m_{gg} \geq 2m_t$.

ATLAS' measured $t\bar{t}$ cross section at $\sqrt{s} = 13$ TeV is $\sigma = 826.4 \pm 3.6(\text{stat.}) \pm 11.5(\text{syst.}) \pm 15.7(\text{lumi}) \pm 1.9(\text{beam})$ pb [24], in good agreement with the NNLO+NNLL prediction of $\sigma = 832^{+40}_{-45}$ pb [25, 26], whereas for $\sqrt{s} = 13.6$ TeV the NNLO+NNLL theoretical cross section is 924^{+32}_{-40} pb [26]. This last theoretical prediction has been confirmed by ATLAS' first Run-3 measurement [27], which, despite using only 11.3 fb^{-1} of data, provided a measurement of $\sigma = 859 \pm 29$ pb. In Figure 2.3 it is represented the measured $t\bar{t}$ production cross section at different values of $\sqrt{s}$, alongside the NNLO+NNLL prediction.

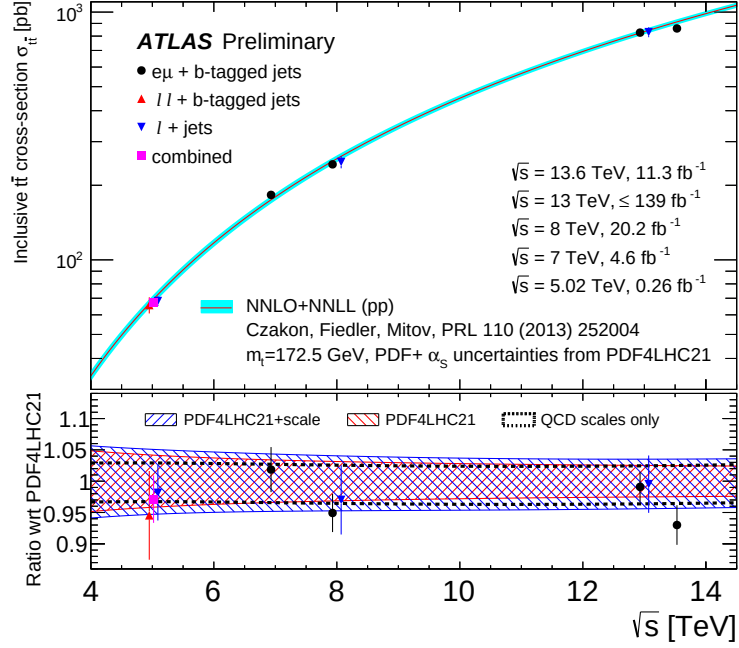


Figure 2.3: Comparison of the measured $t\bar{t}$ cross-sections at various centre-of-mass energies and the theory predictions using the PDF4LHC21 PDF set. The bottom panel shows the ratio of the measured values and three predictions that either contain only the uncertainties originating from the QCD scale variations (black), only the variations in the PDF uncertainties (red) or the total uncertainty in the prediction (blue) [27].

2.2.2 Single top production

Another *top* quark production process is the electroweak *single top production*. Being electroweak, it is less likely to occur with respect to the strong pair production, and it also violates the flavour. There are three different processes that can generate the production of a single *top* quark: *t-channel*, *tW* and *s-channel*. A summary of the the three single *top* quark production cross sections for different values of $\sqrt{s}$ is reported in Figure 2.4.

t-channel

The *t-channel* process is the leading one for single *top* production at hadron colliders (Figure 2.5(a)). It occurs through the t-channel exchange of a virtual *W* boson between an up-type quark (*up* or *charm*) and a *bottom* quark, with the *b* quark taken either by gluon splitting $g \rightarrow b\bar{b}$ in four-flavour scheme (4FS), or as a part of the proton in five-flavour scheme (5FS). A Feynman diagram of the process can be seen in Figure 2.5(a). Its theoretical NNLO cross section at $\sqrt{s} = 13 \text{ TeV}$ is $\sigma = 214^{+4.1}_{-2.6} \text{ pb}$ [29], and it has been measured by both the ATLAS Collaboration [30] and by the CMS Collaboration [31], and both measurements are compatible with the prediction, being respectively $247 \pm 46 \text{ pb}$ and $207 \pm 31 \text{ pb}$.

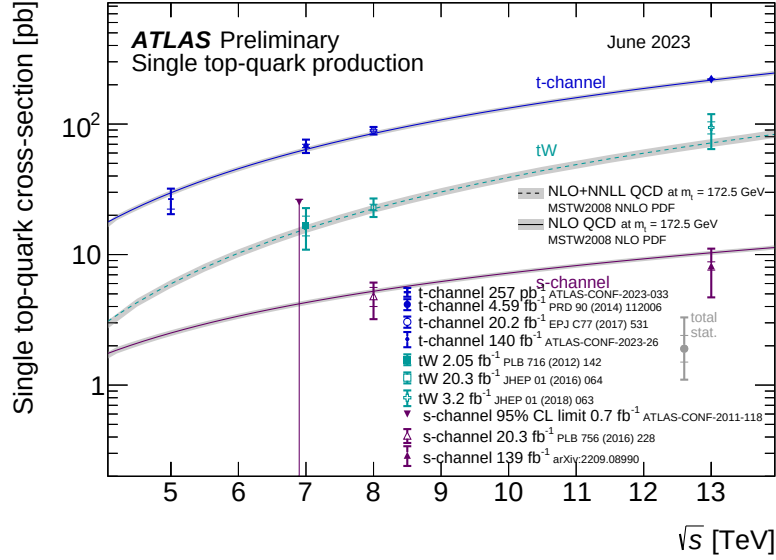


Figure 2.4: Summary of ATLAS measurements of the single top production cross-sections in various channels as a function of the center of mass energy. The measurements are compared to theoretical calculations based on NLO QCD and on NLO QCD complemented with NNLL resummation [28].

tW

tW is the second-leading production process for single- top (Figure 2.5(b)) at the LHC. The final state consists of a real W boson and a top quark, achieved via a s-channel exchange of a virtual $bottom$ quark from an initial state consisting of a $gluon$ and another b quark. Similarly to t -channel, its cross section has been measured by both ATLAS [32] at $94 \pm 10(\text{stat})_{-22}^{+28}(\text{syst}) \pm 2(\text{lumi})$ pb and CMS [33] at $63.1 \pm 1.8(\text{stat}) \pm 6.4(\text{syst}) \pm 2.1(\text{lumi})$ pb, both in agreement with the SM NNLO prediction of $79.3_{-2.8}^{+2.9}$ pb at $\sqrt{s} = 13$ TeV [34].

s-channel

Finally, single top quarks can be produced by the s-channel exchange of a virtual W boson (Figure 2.5(c)). The process has a $q\text{-}\bar{q}'$ initial state, with the two quarks belonging to the same $SU(2)_L$ isospin doublet, and a final state with top and $antibottom$. The NNLO predicted cross section is $11.03_{-0.05}^{+0.08}$ pb [35], confirmed at $\sqrt{s} = 13$ TeV by ATLAS only [36] ($\sigma = 8.2_{-2.9}^{+3.5}$ pb).

2.2.3 Associated productions

Finally, the unprecedented integrated luminosity collected by LHC experiments has allowed for measurements of rare top quark associated production processes. All these processes have at least one electroweak vertex, which is what makes them so rare, and sometimes they can be particularly hard to observe because of a very complex final state.

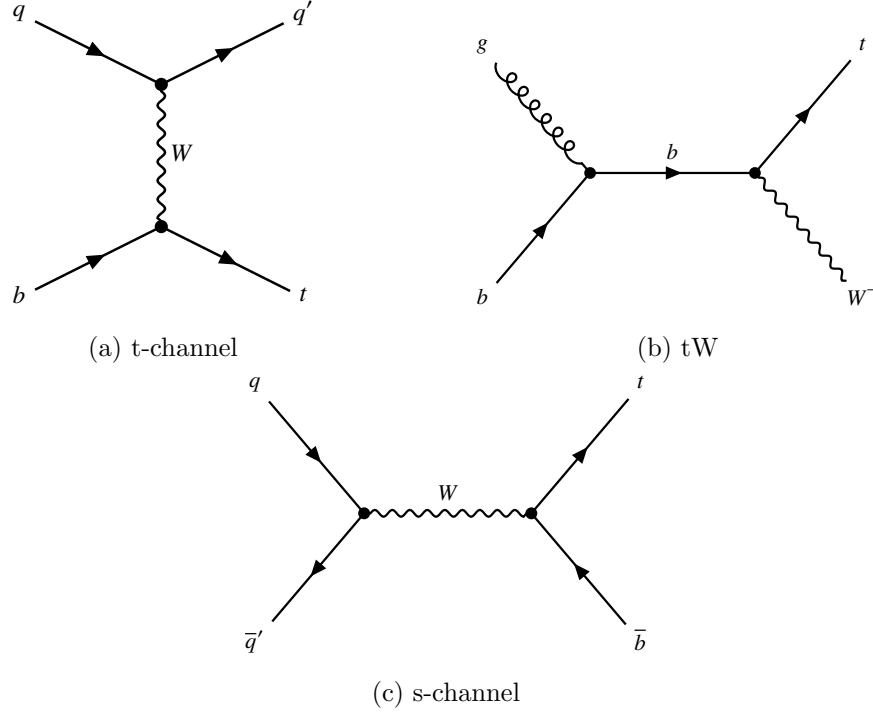


Figure 2.5: Feynman diagram for the single top production

The most interesting processes for this thesis are $t\bar{t}Z$, $t\bar{t}W$, $t\bar{t}H$, tWZ , 4 tops, of which examples LO Feynman diagrams can be seen in Figure 2.6, and finally tZq .

$t\bar{t}Z$

Among all the quoted processes, the leading one is the $t\bar{t}Z$ associated production. It can occur through *top* quark annihilation or Final State Radiation (FSR), with both processes having a $gt\bar{t}$ QCD and a tZ EW vertex. The cross section has been recently measured by the ATLAS experiment at $\sqrt{s} = 13$ TeV as $\sigma = 0.99 \pm 0.05(\text{stat.}) \pm 0.08(\text{syst.})$ pb [37], in agreement with the predicted value of $0.84^{+0.09}_{-0.10}$ pb.

$t\bar{t}W$

After $t\bar{t}Z$, $t\bar{t}W$ is the second-leading associated production process at $\sqrt{s} = 13$ TeV, with a predicted cross section of 72^{+71}_{-78} fb. The most recent ATLAS result comes from the Moriond conference in March 2023 [38, 39], and it provides a mild tension with the NLO prediction, with a measured cross section of 890 ± 85 fb, 1.8σ apart from theory.

$t\bar{t}H$

$t\bar{t}H$ is, alongside *gluon-gluon fusion*, VBF and *Higgsstrahlung*, one of the four processes for Higgs boson production at LHC, being the one with the lowest branching ratio (0.6%).

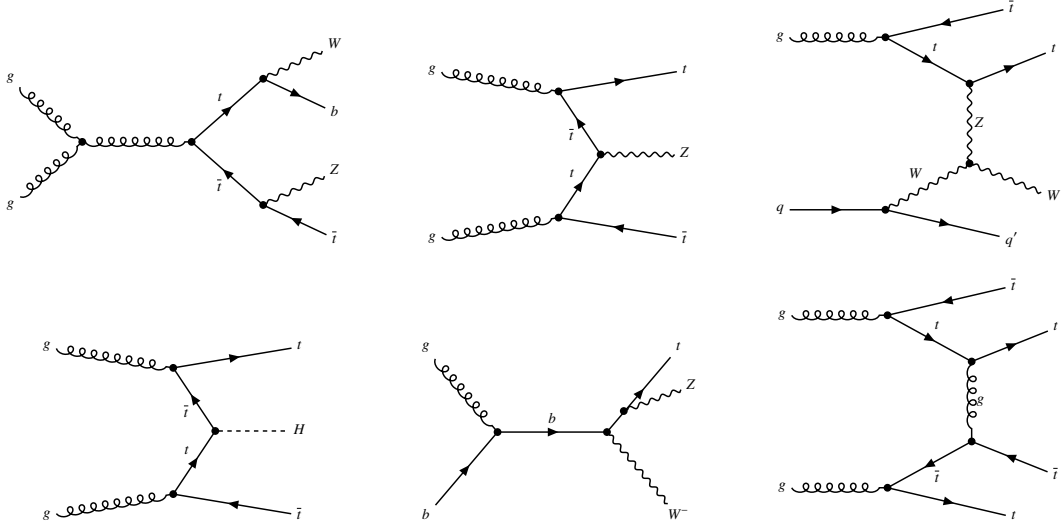


Figure 2.6: Example Feynman diagrams for associated production processes. Top row displays $t\bar{t}Z$ FSR, $t\bar{t}Z$ quark annihilation and $t\bar{t}W$, whereas bottom row shows $t\bar{t}H$, tWZ and 4-tops

It has been observed in 2019 [40], with a cross section of $670 \pm 90(\text{stat.})_{-100}^{+110}(\text{syst.})$ fb, in agreement with SM NLO+NLL prediction of 507_{-50}^{+35} fb [41].

tWZ

This process has yet not been observed, mostly due to the complex final state with two neutrinos, because it involves the production of both a W and a Z boson, alongside a top quark, which subsequently decays into another W boson. Searches have been made in the trilepton (which has only one neutrino, but has 3 jets) and in the tetra-lepton (has 2 neutrinos and 1 b -jet) final states, and just recently CMS has reported evidence for the production, with a measured cross section of $\sigma = 0.37 \pm 0.05(\text{stat}) \pm 0.10(\text{syst})$ pb [42]. The theoretical cross section for this process at $\sqrt{s} = 13$ TeV is $\sigma \simeq 160$ fb [43].

4-tops

Finally, the 4- $tops$ ($t\bar{t}t\bar{t}$) production is one of the hardest processes to observe, due to its low cross section, because it requires a total invariant mass equal to four times the top quark mass, $m_{t\bar{t}t\bar{t}} \simeq 690$ GeV, and to its very complex final state, with 4 b -jets. Nevertheless, the observation has been made [44], with a measured cross section of $\sigma = 22.5_{-5.5}^{+6.6}$ fb, 1.8σ away from the theoretical NLO+NLL prediction of $\sigma = 13.4_{-1.8}^{+1.0}$ fb [45].

2.2.4 tZq

The tZq is the process I am focusing on in this thesis. It is an electroweak process observed by both ATLAS [46] and CMS [47] at $\sqrt{s} = 13$ TeV with an integrated luminosity of

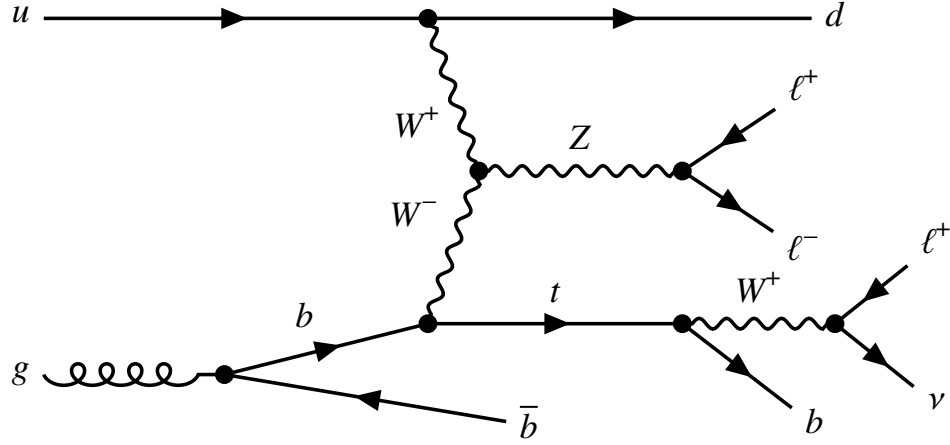


Figure 2.7: Example Feynman diagram for the tZq production with three lepton final state in four-flavour scheme

139 fb^{-1} . It involves the t-channel production of a single *top* quark associated with a Z boson, which can come either from a WWZ triple gauge coupling (Figure 2.7) or from a Z boson emitted from any quark line in the diagram, with Figure 2.8 providing an example of the Z boson emitted by the *top* quark.

The interested final state for this analysis is the *trilepton* final state, achieved when both the Z and W boson (coming from the *top* quark) decay leptonically, thus generating a $t\ell^+\ell^-q$ final state. The NLO theoretical cross section for this process, considering an invariant mass of non-resonant lepton pair $m_{\ell\ell} > 30 \text{ GeV}$, is $\sigma = 102^{+5}_{-2} \text{ fb}$. ATLAS' result is in agreement with this prediction, having measured a cross section of $\sigma = 97 \pm 13(\text{stat.}) \pm 7(\text{syst.}) \text{ fb}$. The purpose of this thesis is to improve this measurement, especially in lowering the uncertainty on the inclusive cross section. Example LO Feynman diagrams for the trilepton final state can be seen in Figures 2.7 to 2.9, where the latter represents the non-resonant process.

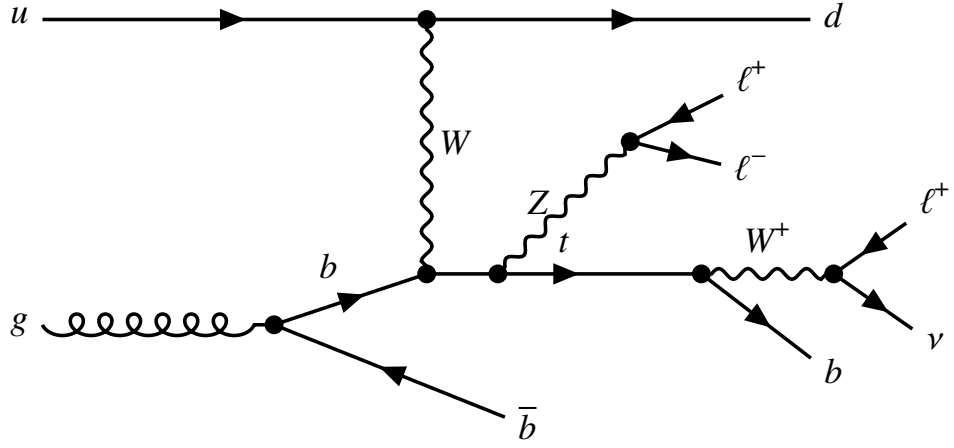


Figure 2.8: Example Feynman diagram for the tZq production with three lepton final state in four-flavour scheme

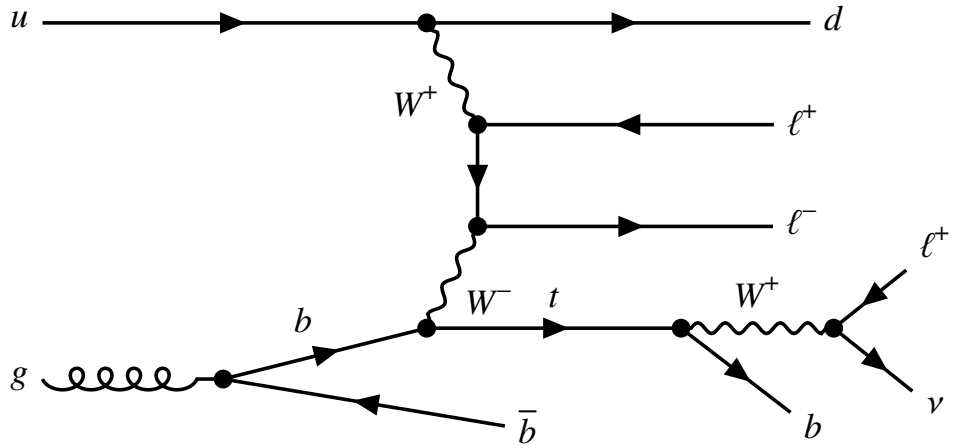


Figure 2.9: Example Feynman diagram for the non-resonant $t\ell\ell q$ production with three lepton final state in four-flavour scheme.

Chapter 3

The Large Hadron Collider and the ATLAS Experiment

3.1 The Large Hadron Collider

The Large Hadron Collider (LHC) [48] is the world's largest and most particle accelerator. Active since 2008 as CERN's latest addition to its accelerator complex in Geneva, the LHC is a 26.7 km ring built in the underground tunnels where once was LEP (Large Electron-Positron), at an average depth of 100 m. As per its specifics, the LHC was built so that it could accelerate two proton beams in different directions and make them collide at $\sqrt{s} = 14$ TeV. Nevertheless, LHC's centre of mass energy is yet to reach that value. When it first started in 2011, the centre of mass energy was half of it, $\sqrt{s} = 7$ TeV, then it got to $\sqrt{s} = 13$ TeV for Run-2 and finally for Run-3 it got closer to its nominal value, reaching $\sqrt{s} = 13.6$ TeV. The LHC can also accelerate and collide heavy ion beams at a centre of mass energy of $\sqrt{s_{NN}} = 5.5$ TeV.

In Figure 3.1, a scheme of the collider ring with its four main experiments is shown, whereas Figure 3.2 displays a scheme of the whole accelerator complex. The protons are first accelerated by LINAC-2 (now replaced with LINAC-4 for Run-3), a linear accelerator that rises their energy up to 50 MeV. Afterwards, protons are accelerated inside the Proton Synchrotron Booster (PSB), a 157 m ring which then leads the protons toward the Proton Synchrotron, whose job is to accelerate protons from 1.4 GeV to 26 GeV. This high energy protons are then brought to the Super Proton Synchrotron (SPS), the second-largest ring at CERN, with a 7 km ring which brings protons energy up to 450 GeV. Finally, the proton beam enters the Large Hadron Collider (LHC), where protons are accelerated up to 6.5 TeV (6.8 TeV for Run-3) before the beams collide in four different points, where four experiments are located:

- ATLAS (*A Toroidal LHC ApparatuS*) [49].
- CMS (*Compact Muon Solenoid*) [50].

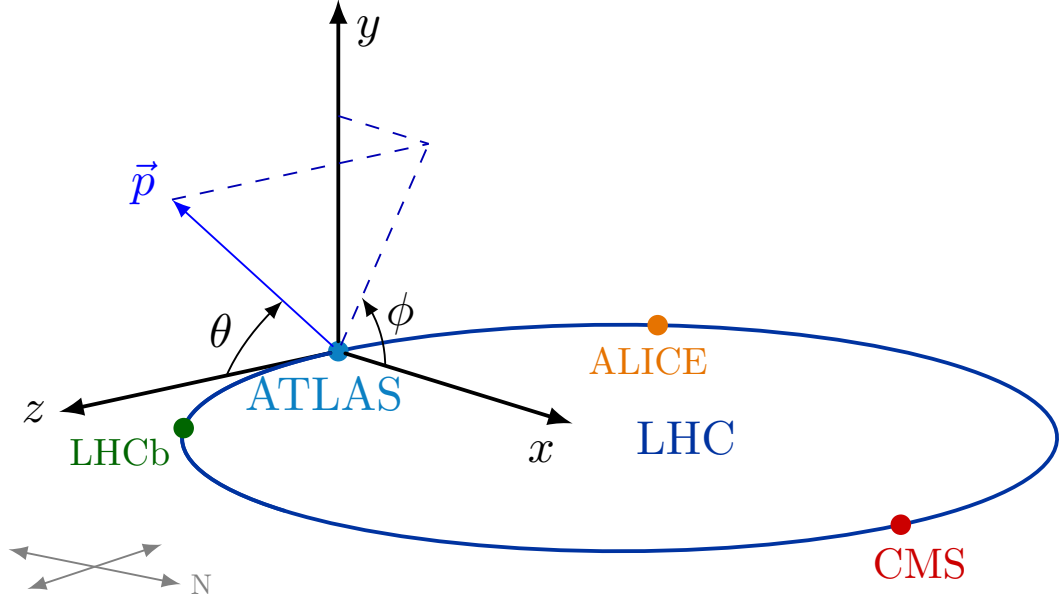


Figure 3.1: A scheme showing the position of the 4 main LHC experiments

- ALICE (*A Large Ion Collider Experiment*) [51].
- LHCb (*LHC beauty*) [52].

ATLAS and CMS are two similar experiments, both aiming at a better understanding of the SM and at searching new physics Beyond SM. On the other hand, ALICE studies the high energy interactions between heavy ions in a plasma state, whereas LHCb explores the heavy flavour physics.

3.1.1 Properties

Center of mass energy

The maximum centre of mass energy reached by the LHC was $\sqrt{s} = 13$ TeV during Run-2 and $\sqrt{s} = 13.6$ TeV for Run-3, even though this value could theoretically go up to 14 TeV. A higher centre of mass energy allows for a better probing of the internal structure of the proton.

Bunches

The protons running inside LHC's ring are stored in bunches. For the Run-2 data taking period, each bunch was made of 1.2×10^{11} and was 25 ns away from the closest bunch. During that period, there were 2500 bunches for proton beam.

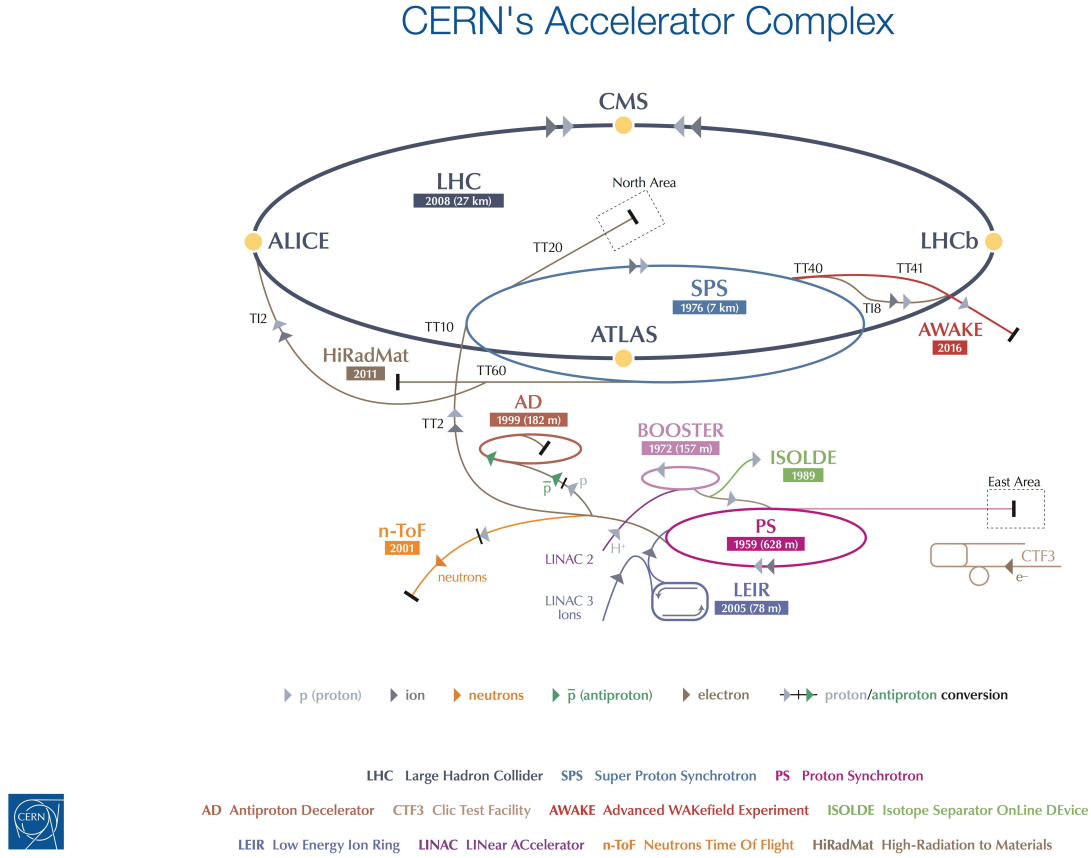


Figure 3.2: A schematic view of the acceleration chain at CERN.

Frequency of collisions

After they are accelerated, proton beams are collided at the four main LHC experiments. During Run-1, the frequency of collision was 20 MHz, whereas in Run-2 this figure has been increased to 40 MHz [53].

Magnets

The LHC ring uses Magnets to bend and focalise the beam and RF cavities to accelerate it. The ring has 9593 magnets, of which 1232 dipoles, used to deflect the beam, and 392 quadrupoles, used to focalise it. This superconducting magnets operate at temperatures above 1.9 K, generating fields of around 7.7 T [48].

RF cavities

In order to accelerate the beam, LHC uses eight RF cavities, which produce an electric field of frequency $\nu = 400.8$ MHz [53].

Instantaneous Luminosity

For the purpose of a cross section measurement, it is important to know the Luminosity delivered by the collider. Luminosity is defined as the proportional constant between the rate of events R and its cross section σ , as $R = L\sigma$. Therefore, Luminosity is measured in $\text{b}^{-1}\text{s}^{-1}$, and is defined as $L = n_b N_1 N_2 F / 4\pi\epsilon\beta^*$ ⁸. By definition, a higher Luminosity allows for more statistics, thus increasing the likelihood of rarer events to happen. During Run-2, the Luminosity delivered by the LHC peaked at $L = 2 \times 10^{10} \text{ b}^{-1}\text{s}^{-1}$ [54].

Integrated luminosity

Since data tells us the total number of events instead of the rate, it is even more important to look at the integrated luminosity, which is the integral of luminosity over time. Because of the cross section being time-independent, when integrating the formula for the rate $R = L\sigma$, we get $\int R dt = N = \sigma \int L(t) dt$, where N is the number of total events and $\int L(t) dt$ is the integrated luminosity. Therefore, the integrated luminosity is the proportional constant between the number of events and the cross section. Its unit of measure is the inverse barn b^{-1} . In Figure 3.3 we can see the delivered luminosity over time in different years of data-taking. For this thesis, I will be analysing the full Run-2 data, that is data taken between 2015 and 2018. The integrated luminosity of the full Run-2 data-taking period events is $140.1 \pm 1.2 \text{ fb}^{-1}$ [55], as can be seen in Figure 3.4, split into 3.24 fb^{-1} for 2015, 33.40 fb^{-1} for 2016, 44.6 fb^{-1} for 2017 and 58.8 fb^{-1} for 2018.

Pileup

For pileup we refer to the phenomena that occurs when multiple proton-proton collisions take place in the same time window of 25 ns in which two proton bunches collide. This interactions are usually low- Q^2 inelastic interactions occurring in the same bunch crossing, alongside the hard scattering process. As a consequence of this, there are multiple interactions that overlap in the detector, thus increasing the number of particles inside the detector. μ refers to the number of interaction per crossing, that is the number of additional collisions occurring during a beam collision, and it increases with Luminosity, because the higher the Luminosity is, the higher the collision rate is. For Run-2, on average there were $\langle\mu\rangle = 33.7$ interactions per crossing, as can be seen from Figure 3.5.

3.2 The ATLAS experiment

The ATLAS (*A Toroidal LHC Apparatus*) experiment has been active since 2008, aiming at the study of both SM and BSM processes analysing proton-proton collisions. The

⁸ n_b is the number of colliding bunches, N_i refers to the number of protons per bunch ($i = 1, 2$), ϵ is the beam emittance, the β^* factor considers the focus of the magnets and finally F is the geometric luminosity reduction factor due to the crossing angle at interaction point.

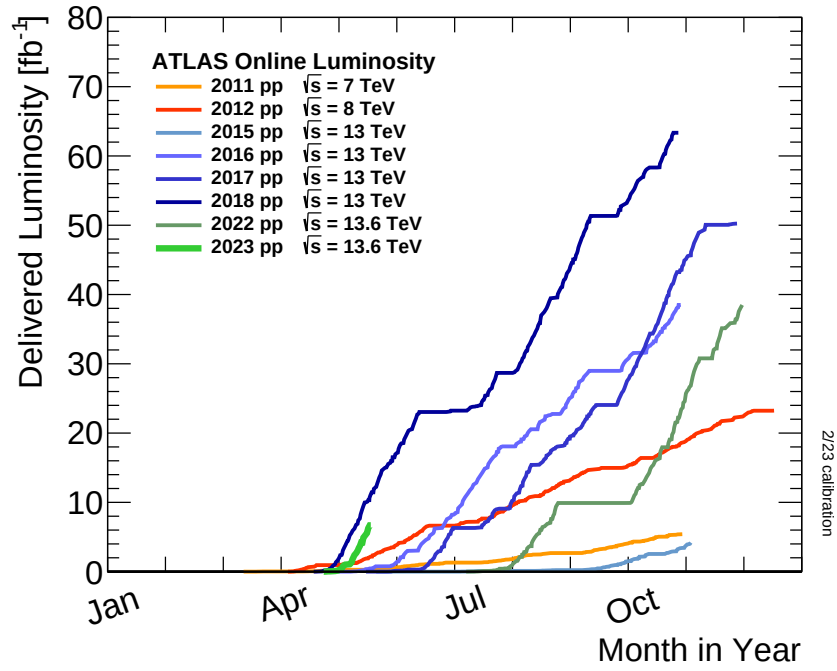


Figure 3.3: Cumulative luminosity versus day delivered to ATLAS during stable beams and for high energy p-p collisions [57].

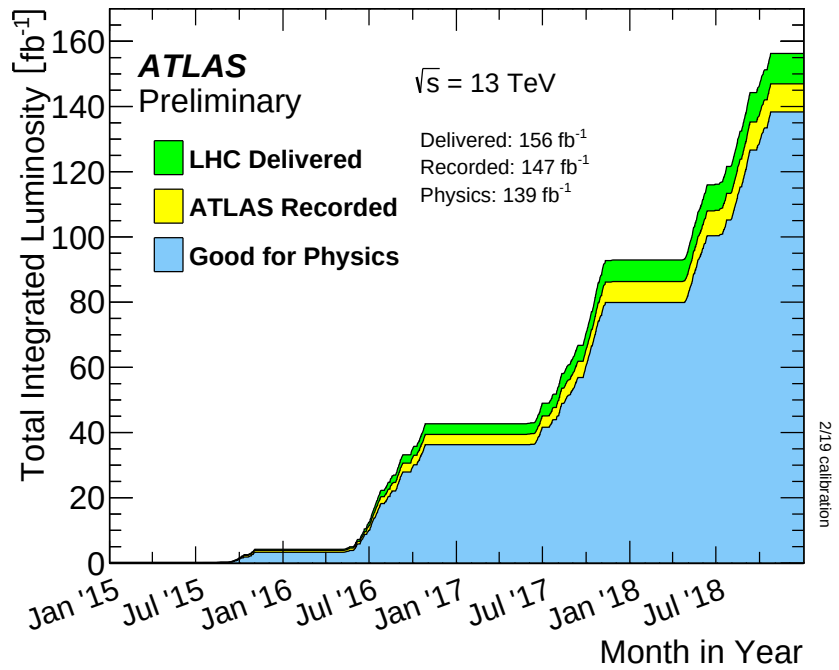


Figure 3.4: Cumulative luminosity versus time delivered to ATLAS (green), recorded by ATLAS (yellow), and certified to be good quality data (blue) during stable beams for pp collisions at 13 TeV centre-of-mass energy in 2015-2018 [57].

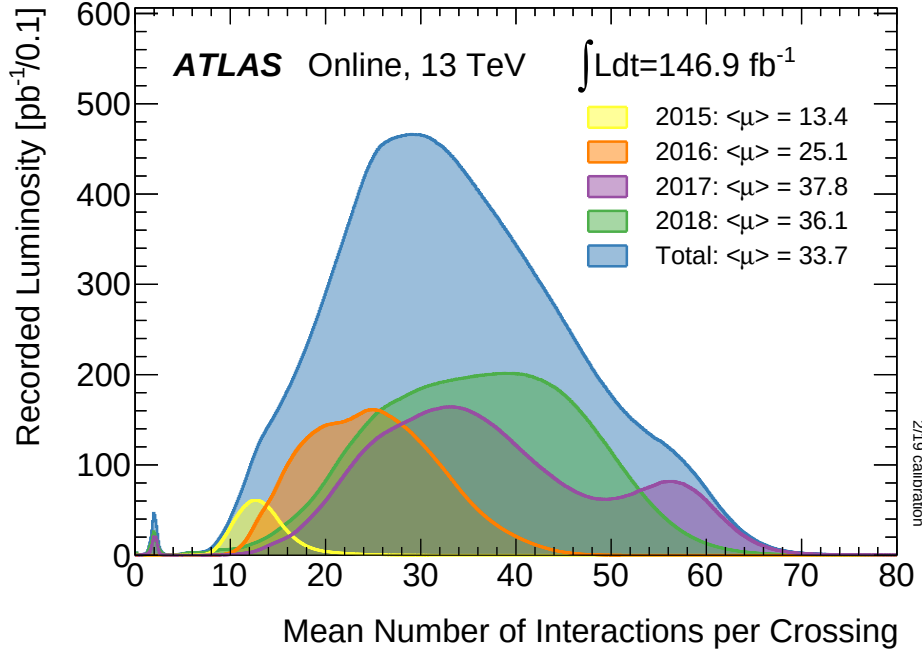


Figure 3.5: Luminosity-weighted distribution of the mean number of interactions per crossing for the 2015-2018 pp collision data at $\sqrt{s} = 13$ TeV. The integrated luminosity and the mean μ value are shown separately for each year [57].

ATLAL detector (Figure 3.6), with its 46 meters length and 25 meter width, is the biggest detector at LHC, weighting 7000 tonnes and located 100 meters below ground [58]. A complete description of the ATLAS detector can be found in [49]. As represented in Figure 3.1, the detector has a cylindrical symmetry, thus surrounding almost completely the interaction point, with the x-axis pointing toward the centre of the ring and the z-axis following the beam direction. The polar angle θ is defined from the z-axis, whereas the azimuthal angle ϕ is measured from the x-axis around the beam. Transverse quantities, such as the transverse momentum p_T , are measured along the x-y plane, and carry the property of being invariant under interaction reference frame (IRF) boosts. An additional quantity used in ATLAS analyses is the pseudorapidity η , defined as in Equation (3.2.1).

$$\eta \doteq -\ln \left(\tan \left(\frac{\theta}{2} \right) \right) \quad (3.2.1)$$

The pseudorapidity is used instead of the polar angle θ because $\Delta\eta$ is invariant with respect to IRF boosts. In addition to this, η provides a 1-to-1 map with θ , with $\eta(\theta = \pm\pi) = \pm\infty$, and it is easier to measure than the rapidity Y . The pseudorapidity also allows for a simpler definition of the invariant mass $m_{12}^2 \doteq (E_1 + E_2)^2 - (\vec{p}_1 + \vec{p}_2)^2$, which can be written as $m_{12}^2 = 2p_{T_1}p_{T_2}(\cosh \Delta\eta - \cos \Delta\phi)$. Finally, the distance R is defined in the $\eta - \phi$ plane, as $\Delta R = \sqrt{\Delta\eta^2 + \Delta\phi^2}$.

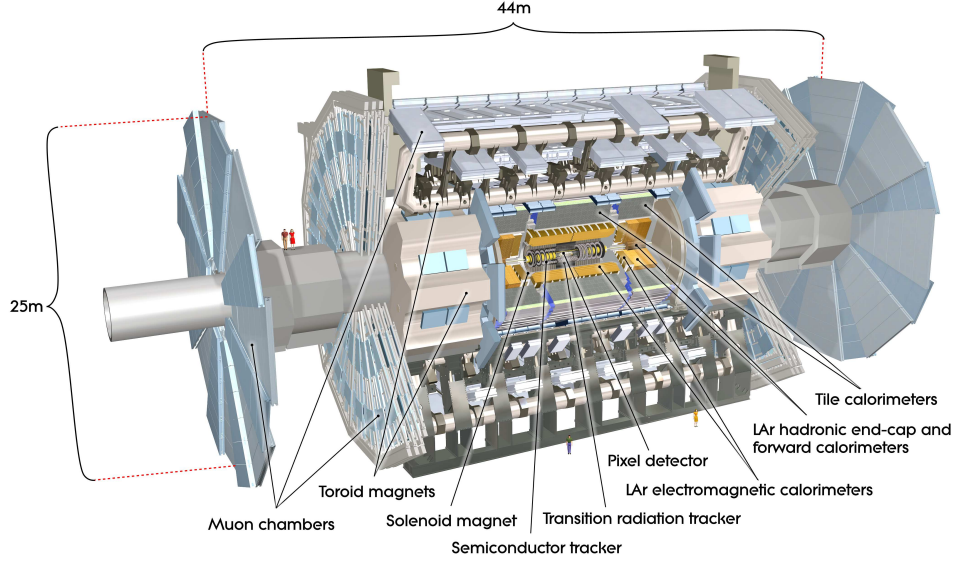


Figure 3.6: Cut-away view of the ATLAS detector [49].

The ATLAS detector is made of different layers of subsystems, each of them targeting a different type of particles:

- Inner Detector (ID). It is the closest system to the interaction point. It is embedded in a 2 T solenoidal magnetic field, so, by measuring the trajectory of the particles, it provides information about the momentum and the charge of said particles.
- Electromagnetic Calorimeter (ECAL). It surrounds the ID, it generates an electromagnetic shower when an electron or a photon enter it, allowing for a measure of their energy.
- Hadronic Calorimeter (HCAL). It environs the ECAL, its aim is to measure the energy of the hadrons by creating a hadron shower.
- Muon Spectrometer (MS). It is the furthest from the interaction point, surrounding the entire detector. It is embedded in a toroidal magnetic field, it is designed to reconstruct the momentum and trajectory of the muons.

In Figure 3.7 a scheme of how different particles behave in the ATLAS detector, showing the effect of the four subsystem and why they are needed.

The general performance goals of the different layers are summarised in Table 3.1.

3.2.1 The magnets

ATLAS has a system of four large superconducting magnets. The system is 26 m long and 22 m wide, and it stores an energy of 1.6 GJ. ATLAS's magnet system is made of two different types of magnets: the central solenoid (Figure 3.8(a)) and the barrel and

Detector component	Required resolution	η coverage Measurement (Trigger)
Tracking (ID)	$\sigma_{p_T}/p_T = 0.05\%p_T \oplus 1\%$	± 2.5
ECAL	$\sigma_E/E = 10\%\sqrt{E} \oplus 0.7\%$	$\pm 3.2 (\pm 2.5)$
HCAL barrel and end-cap forward	$\sigma_E/E = 50\%\sqrt{E} \oplus 3\%$ $\sigma_E/E = 100\%\sqrt{E} \oplus 10\%$	± 3.2 $3.1 < \eta < 4.9$
Muon Spectrometer	$\sigma_{p_T}/p_T = 10\%$ at $p_T = 1$ TeV	$\pm 2.7 (\pm 2.4)$

Table 3.1: General performance goals of the ATLAS detector [49]. When not stated otherwise, the η trigger value is the same as the measurement one.

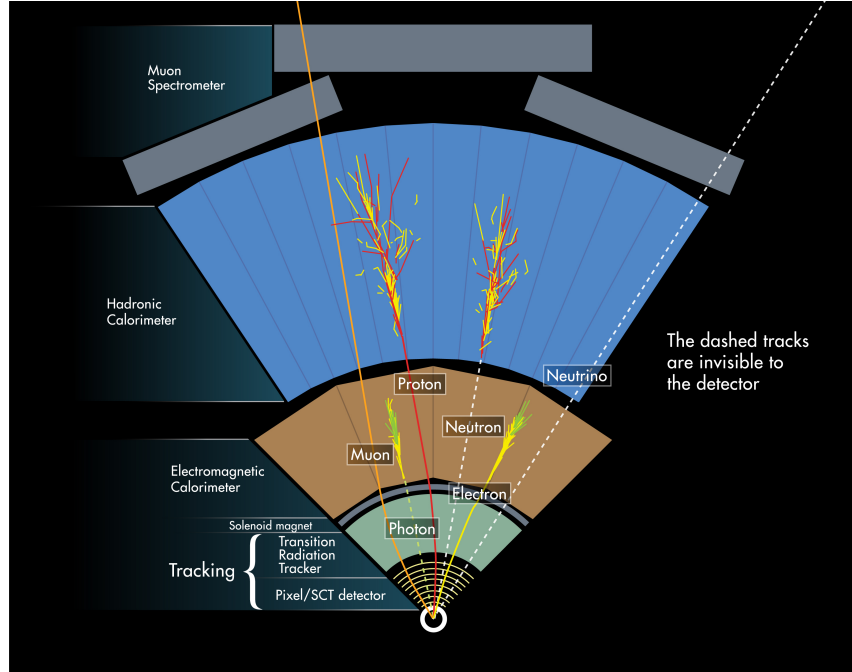
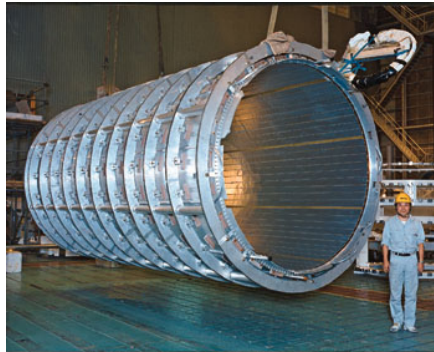
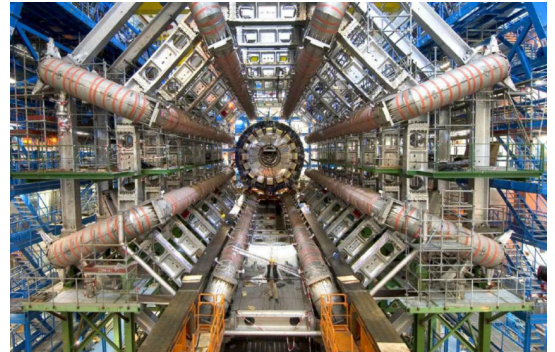


Figure 3.7: Diagram of particle paths in the ATLAS detector [59].



(a)



(b)

Figure 3.8: Photos of the magnets of the ATLAS experiment: the central solenoid (Figure 3.8(a)) and the barrel toroid (Figure 3.8(b)) [49].

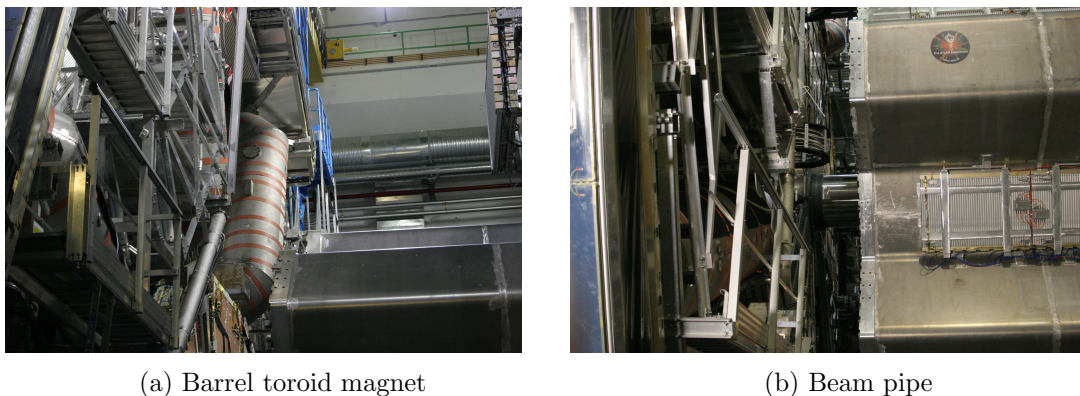


Figure 3.9: Pictures of the barrel toroid magnet mounted in the detector and of the beam pipe, taken during the 2022 YETS.

end-caps toroids (Figure 3.8(b)). A photo of a mounted barrel magnet taken during the Run-3 data taking period, can be seen in Figure 3.9(a).

The toroid system, responsible for the magnetic field of the Muon Spectrometer, is made of three magnets: the barrel (Figures 3.8(b) and 3.9(a)) and two end-cap toroids. The field generated by the toroids is centred on the beam axis. The barrel toroid provides 1.5 to 5.5 Tm of bending power in the range $|\eta| < 1.4$, whereas the end-cap toroids provide 1 to 7.5 Tm of bending power in the range $1.6 < |\eta| < 2.7$. In the overlap region $1.4 < |\eta| < 1.6$, the bending power is lower. On the other hand, the solenoids provide a 2 T axial magnetic field, orthogonal to the field generated by the toroids.

3.2.2 The Inner Detector

The ATLAS Inner Detector (See Figure 3.10) is designed to provide hermetic and robust pattern recognition, alongside high momentum resolution and both primary and secondary vertex measurements for charged particles with $p_T > 0.5$ GeV, and in the pseudorapidity range $|\eta| < 2.5$. It is made of three different sub-detectors:

- Pixel detector. It is the closest detector to the collision point, and it consists of four barrel layers and two end-caps regions, for a total of 10^8 silicon pixels, each of the size $50 \times 400 \mu\text{m}^2$. This detector provides four different measurement points for particles with tracks with $|\eta| < 2.5$, and it also has a full coverage in ϕ . The fourth layer (IBL) was installed in 2014 at $R = 33.25$ mm, making it the closest one to the beam, thus allowing four measurement points instead of three, as it was for Run-1. When a charged particle passes through Silicon, it generates electron/hole pairs, which then drift in the electric field generated by the p-n junction of doped Silicon, inducing a signal which gives position information.
- SemiConductor Trackers (SCT). Likewise, this detector is made of silicon sensors, however they have a wider segmentation than the ones in the Pixel detector. It entirely surrounds the Pixel detector with four barrel layers and two end-caps, for a

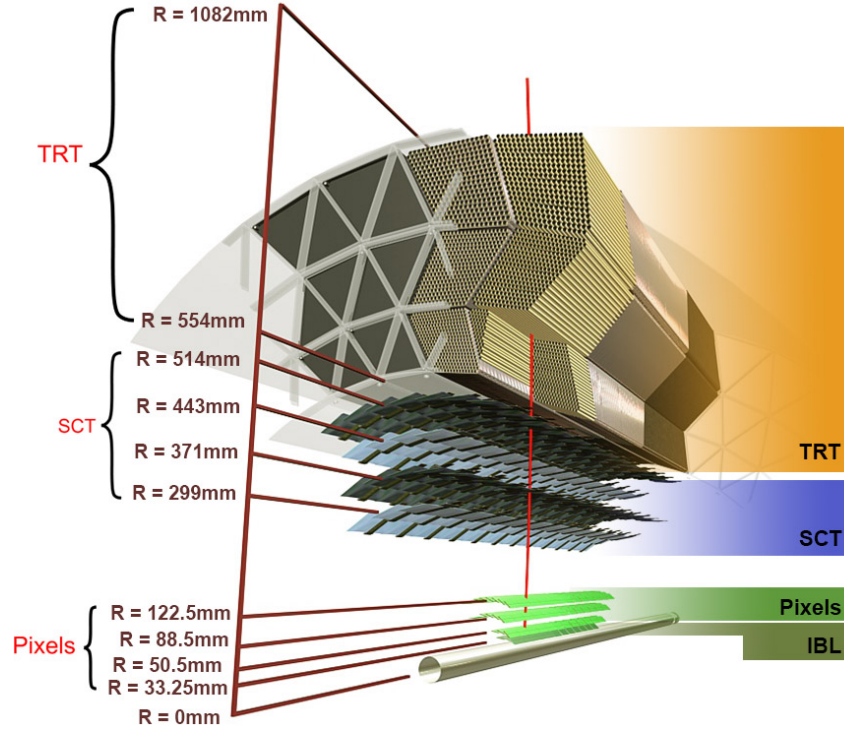


Figure 3.10: Drawing showing the sensors traversed by a charged particle in the Inner Detector [49].

total of 6×10^6 silicon strips. The SCT operates at a temperature of -7°C , same as the Pixel detector.

- Transition Radiation Tracker (TRT). It is the outermost system of the ID and it includes almost 400.000 proportional drift tubes (straws) in 73 layers. The TRT was designed so that particles with $p_T > 0.5 \text{ GeV}$ and $|\eta| < 2$ cross typically more than 30 straws. Transition radiation occurs when a relativistic particle passes through two media with a different refraction index, with the energy of the emitted radiation that depends on the γ factor. Therefore, the TRT can also be used for particle identification.

The ID is fully immersed in a solenoidal 2 T magnetic field generated by the Central Solenoid (CS), which operates at a temperature of 4.5 K.

3.2.3 The calorimeter system

The calorimeter system (See Figure 3.11) includes both the Electromagnetic Calorimeter (ECAL) and the Hadron Calorimeter (HadCAL). The former is used to study of photons and electrons, whereas the latter is dedicated to the measurement of hadrons. They both cover the same pseudorapidity range $|\eta| < 4.9$.

The main purpose of the calorimeter system is to measure both energy and posi-

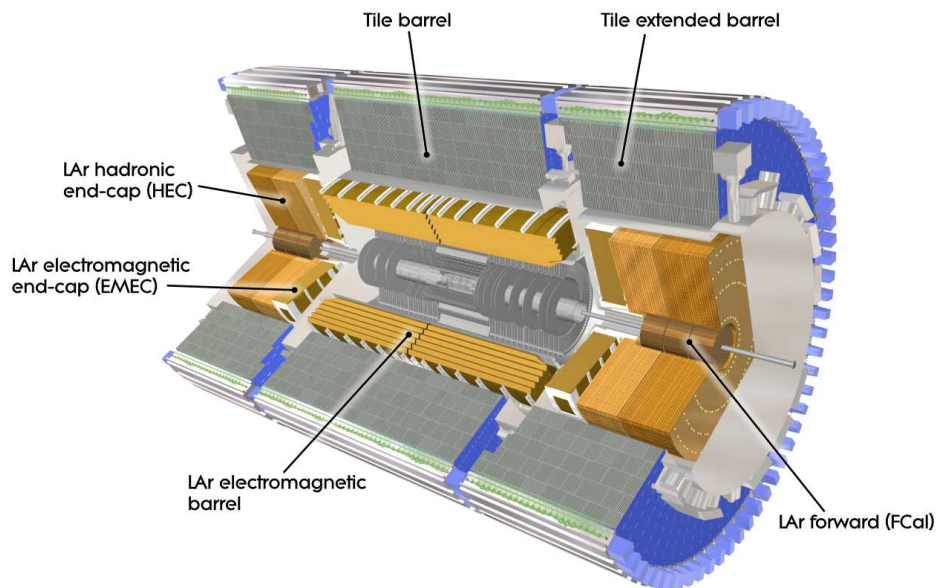


Figure 3.11: A schematic view of the calorimeter system of the ATLAS Experiment [49].

tion of the particles, and it does that having good containment for both electromagnetic and hadronic showers. Therefore, ECAL's thickness is more than 25 radiation lengths (X_0), thus causing a containment of 2/3 of a typical hadronic shower. The rest of the calorimeter is designed for missing energy and jet reconstruction. The total thickness of the ECAL+HCAL system is $\sim 10\lambda$, with λ being the interaction length, which is wide enough to reduce punch-through into the muon system.

The Electromagnetic Calorimeter is a sampling calorimeter, where lead acts as the absorber and liquid Argon (LAr) is the active media. The absorbers are accordion-shaped, thus allowing for complete ϕ symmetry without azimuthal cracks. It is 47 cm long, equal to almost 25 X_0 , and it provides coverage in $|\eta| > 3.2$. In order to have also position information, fine longitudinal segmentation was also implemented, with a first layer of strips which provide π_0 rejection, as well as high granularity, with more than 200.000 readout channels.

The Hadronic Calorimeter is made of three different systems. The Tile Calorimeter, which uses Steel in order to generate scintillation radiation, is placed directly outside the ECAL. The other two systems are the LAr hadronic end-cap calorimeter, which consists of two independent wheels per end-cap and it is located behind the ECAL end-caps, and the LAr forward calorimeter (FCal), which is integrated into the end-cap. The FCal, with its 10 interaction length depth, reduces the radiation background levels in the muon spectrometer, and it is made of three different modules, one made of Copper, which is optimised for electromagnetic measurements, and two made of Tungsten, specialised in hadronic energy measurements. All in all, the HadCAL provides a pseudorapidity coverage of $|\eta| < 4.9$.

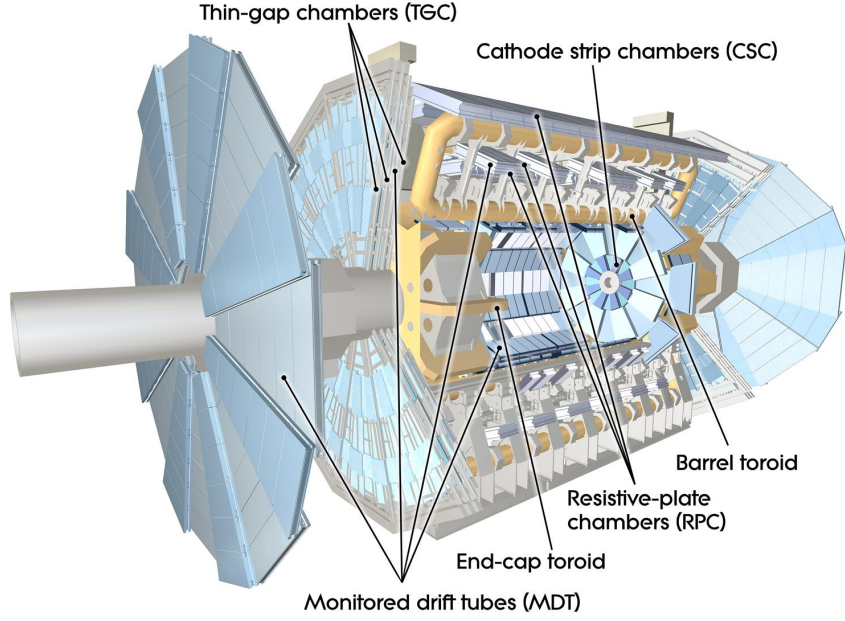
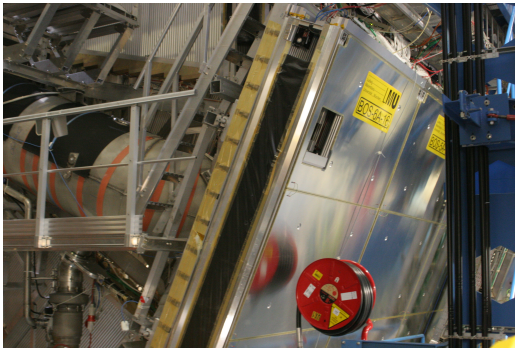


Figure 3.12: Cut-away view of the ATLAS muon system [49].

The detection process works as follows: incident particles shower in the absorber material, ionising the LAr and generating electrons. The electrons then drift in an electric field, inducing a signal in the read out electrodes. Photomultipliers are also used to amplify the signal, thus generating a measurable output.

3.2.4 The Muon Spectrometer

Finally, the Muon Spectrometer (MS) (Figure 3.12) is the outermost detector of the ATLAS experiment. It is made of 4.000 muon chambers, of which photos can be seen in Figure 3.13. Since the calorimeters are not designed to stop muons, the MS is needed,



(a) Resistive plate chambers



(b) Thin gap chambers

Figure 3.13: Pictures of the muon chambers mounted in the ATLAS detector, taken during the 2022 YETS.

especially to provide transverse momenta measurement and muon trigger. In order to measure the transverse momentum, it is immersed in the toroidal magnetic field generated by the barrel. Therefore, since muons are bent by the field, it is possible to measure the sagitta s , which allows for p_T measurement, as $p_T = L^2 q B / 8s$, where L is the length of the trajectory, B is the magnetic field and q is the charge of the muon.

Similarly to the calorimeter system, the MS is divided into three regions, a barrel and two end-caps, for a total pseudorapidity coverage of $|\eta| < 2.7$.

3.2.5 Trigger system

ATLAS uses a two-levels trigger to select events: a hardware-based level (L1) and a software-based High-Level Trigger (HLT).

The initial event selection is performed by the L1 trigger, which reduces the rate of incoming data from 40 MHz to 100 kHz. Calorimeter selections (electrons, photons and jets) are based on reduced-granularity information provided by both ECAL and HadCAL, whereas muons are identified in the spectrometer, using dedicated trigger chambers. The L1 decision must reach the front-end electronics within 2.5 μ s after the bunch-crossing, providing the HLT with Regions of Interest (RoI), which are the ones where possible trigger objects within the event are identified. Finally, The HLT uses both fast and offline reconstruction algorithms to confirm the trigger decision. The output rate of the HLT trigger is 1 kHz.

3.2.6 Forward detectors

There are other detectors whose aim is to measure the luminosity. The closest one to the interaction point (17 m) is LUCID (LUminosity Cherenkov Integrating Detector, [60]), which detects inelastic pp scattering in the forward direction and it is the main online relative-luminosity monitor for ATLAS. In addition to this, LUCID is also used to check the beam losses before collisions. Additional detectors are ALFA (Absolute Luminosity For ATLAS), located 240 m away from the collision point, and ZDC (Zero-Degree Calorimeter), located at 140 m from the interaction point.

Chapter 4

Analysis setup

In this chapter I will describe the way the analysis has been structured. I will begin with an introduction on the state of the art for the tZq process in Section 4.1. Then, I will report a brief description of the Data (Section 4.2) and Monte Carlo (Section 4.3) samples, followed by a discussion on the object reconstruction process at the ATLAS detector in Section 4.4. Finally, I will give a description of the event selection for this analysis in Section 4.5, before describing the analysis setup in Section 4.6.

4.1 State of the art

The tZq process is a rare electroweak process observed by both ATLAS [46] and CMS [47] in 2018. It is a process involving the t -channel single top quark production associated with a Z boson, coming whether from a WWZ triple gauge coupling or from a Z boson radiation emitted from any line quark in the diagram. Of particular interest is the case when the Z boson is emitted by the top quark, since it allows to have insights on the electroweak coupling between the top quark and the Z boson, which SM predicts to be as in Equation (1.2.2). An additional reason for studying the tZq process is that this is one of the backgrounds to many other processes, mainly the single top production in association with a Higgs boson (tHq), which gives insights on the tH Yukawa coupling, in particular its sign which cannot be measured with $t\bar{t}H$. Furthermore, tZq is a background to $t\bar{t}Z$, another process which can help on the measurement of the tZ coupling, as well as multiple BSM searches. The NLO theoretical cross section is $101.7_{-1.3}^{+5.3}(\text{scale}) \pm 1.1(\text{PDF})$ fb for the trilepton final state at $\sqrt{s} = 13$ TeV.

This thesis describes a continuation of the analysis carried out by the ATLAS Experiment in 2018 [46], to which I will refer as the “previous analysis”. The previous analysis focused on the trilepton final state, obtained when both the Z and W boson (coming from top quark decay) decay leptonically. The cross section was measured for $m_{\ell\ell} > 30$ GeV with an integrated luminosity of 139 fb^{-1} at $\sqrt{s} = 13$ TeV as $\sigma(pp \rightarrow t\ell^+\ell^-q) = 97_{-13}^{+14} \text{ fb} = 97_{-12}^{+13}(\text{stat.}) \pm 7(\text{syst.})$ fb, which has a relative 15.2% uncertainty, dominated by statistics.

The purpose of this thesis is to provide an improved measurement of the inclusive cross section, aiming at reducing the total uncertainty, with the goal of reaching CMS's latest measurement [61], in which a first differential cross section measurement was also presented. Additionally, I will present a first measurement of the ratio between the *top-antitop* cross sections ($R_{t\bar{t}} = \sigma(tZq)/\sigma(\bar{t}Zq)$), which can be compared to the *t*-channel measurement of $1.636^{+0.036}_{-0.034}$ [95].

4.2 Data samples

For this thesis I will be analysing all the data recorded by the ATLAS Experiment during the full Run-2, which occurred between 2015 and 2018. The data corresponds to $\sqrt{s} = 13$ TeV proton-proton collisions with a total integrated luminosity of $140.1 \pm 1.2 \text{ fb}^{-1}$ [55, 56].

The selected data events were collected only when the LHC beams were stable and all ATLAS detectors were operational. The Good Run List (GRL) allows to select only events satisfying these requirements. The GRLs used in this analysis are reported in Table 4.1, alongside the integrated luminosity for each data sample. Additional selection is made by the trigger system. Events were selected only if they passed at least one of the single-electron or single-muon triggers listed in Table 4.2. Electron trigger had a transverse momentum p_T threshold of 24 GeV in 2015, which was then increased to 26 GeV from 2016. Instead, muon trigger required a $p_T > 20$ GeV in 2015, even though this figure was brought to 26 GeV the following year [62–64].

Year	Int. Lumi. (fb^{-1})	Good Run List
2015	3.2	data15_13TeV/20170619/physics_25ns_21.0.19.xml
2016	33.4	data16_13TeV/20170605/physics_25ns_21.0.19.xml
2017	44.6	data17_13TeV/20180619/physics_25ns-Triggerno17e33prim.xml
2018	58.8	data18_13TeV/20181111/physics_25ns-Triggerno17e33prim.xml

Table 4.1: GRL of data samples used in the analysis.

Year	Single e	Single μ
2015	HLT_e24_lhmedium_L1EM20VH HLT_e60_lhmedium HLT_e120_lhloose	HLT_mu20_loose_L1MU15 HLT_mu50
2016-2018	HLT_e26_lhtight_nod0_ivarloose HLT_e60_lhmedium_nod0 HLT_e140_lhloose_nod0	HLT_mu26_ivarmedium HLT_mu50

Table 4.2: Trigger selections [62–64]

4.3 Monte Carlo samples

Monte Carlo (MC) techniques are used in physics analysis in order to simulate the interesting process to provide a prediction of what should be seen by the experiment. In order to be able to evaluate the goodness of the physics result, it is important that the MC simulated samples represent correctly the physics. For the MC generation, multiple theoretical aspects are accounted for, such as proton PDFs, parton showering, renormalisation and factorisation scales, as well as detector response and efficiency.

The MC simulated samples were grouped in three different Monte Carlo simulation campaigns:

- **mc16a:** this campaign contains the MC simulated events meant to reproduce the data collected in 2015 and 2016. These events are scaled to a total integrated luminosity of 36.6 fb^{-1} .
- **mc16d:** this campaign refers to the MC simulated events reproducing the data collected in 2017, with a total integrated luminosity to which they have to be scaled of 44.6 fb^{-1} .
- **mc16e:** this campaign contains the events simulating the data collected in 2018, which corresponds to a total integrated luminosity of 58.8 fb^{-1} .

All events are simulated with a *top* quark mass $m_t = 172.5 \text{ GeV}$ and with a branching fraction of the $t \rightarrow Wb$ decay equal to 1. In the following, I will present a description of both the signal and the SM background samples

4.3.1 Signal sample

The MC simulated signal sample is tZq . The requirement is for both the W and the Z bosons to decay leptonically, thus having a $3\ell 1\nu$ final state, as can be seen in Figures 2.7 and 2.8. This signal considers both *top* and *antitop* (see Figure 4.1) productions, as well as non resonant lepton pair production $t\ell\ell q$ (Figure 2.9). The main difference between the *top* and *antitop* processes is the sign of the lepton coming from the W boson: in the *top* production, we have an antilepton ℓ^+ , because there is a $t \rightarrow W^+ b \rightarrow \ell^+ \nu b$ decay. However, in the *antitop* production there is a lepton ℓ^- , since there is a $\bar{t} \rightarrow W^- \bar{b} \rightarrow \ell^- \bar{\nu} \bar{b}$ decay. What stands out from the comparison between the four Feynman diagrams in Figures 2.7, 2.8 and 4.1 is that the final state has a positively charged lepton (thus having a *top*) when the initial quark that interacts with the b quark coming from gluon splitting is a quark of type “up”, that is, u or c . On the other hand, when the lepton coming from the W boson is negatively charged, leading to *antitop*, the initial state is made of d , s or b . Therefore, the ratio between *top* and *antitop* depends on the PDFs, and thus it varies with the centre of mass energy, as can be seen in Figure 4.2. Because in the proton there are more *up* quarks than *down* quarks, the ratio is bigger than one. However, the ratio is not always equal to 2, as the pre-parton model would have predicted. The higher the

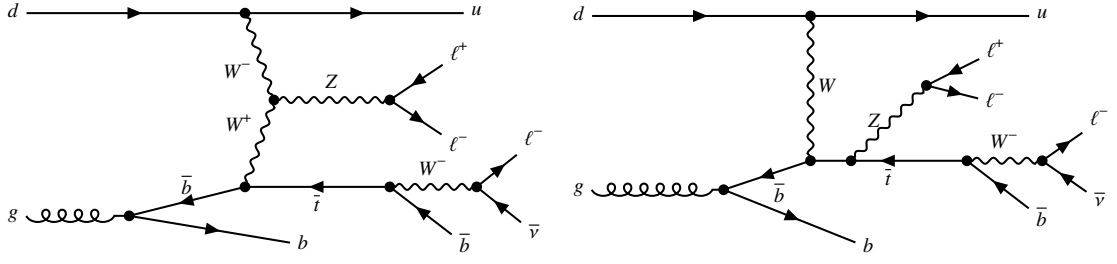


Figure 4.1: Example Feynman diagram for the $\bar{t}Zq$ production with three lepton final state in four-flavour scheme.

energy, the more the internal structure of the proton can be probed, thus allowing for other quarks and antiquarks to take part in the process. Consequently, the ratio decreases with energy. At $\sqrt{s} = 13$ TeV the theoretical ratio is $R_{t/\bar{t}} = 1.6775$, thus favouring the *top* with respect to the *antitop* production.

The signal sample was simulated using the MADGRAPH5_AMC@NLO2.9.5 generator [65] at NLO using the NNPDF3.0NLO PDF set [66]. The sample was interfaced with PYTHIA8.2.45 [67] using the A14 tune [68] and the NNPDF2.3LO PDF set [69]. Factorisation and renormalisation scales are set to $H_T/6$. The process was generated in 4 flavour scheme (FS), meaning the quarks that can be found inside a proton are only u , d , c and s . Therefore, the *bottom* quark that generates a *top* quark can come only from gluon splitting, thus including an additional b -quark in the final state. The sample was then normalised to a cross section obtained in the five-flavour scheme, so considering the *bottom* quark as a possible initial parton in the proton. Additional non-resonant $t\bar{t}^+\ell^-q$ productions are included, with $m_{\ell\ell} > 5$ GeV.

4.3.2 Background samples

The background is made of both reducible and irreducible predicted SM processes. Reducible backgrounds are backgrounds in which one or more particles are non-prompt (fake), for example a lepton which is not generated in the interaction vertex but instead it comes from an hadronic jet. These backgrounds can be reduced using tighter requirements for identification and isolation. On the other hand, irreducible backgrounds are made of processes with the same final state of the signal we are looking for, and therefore the detector cannot know that the event it sees comes from another process.

In the following I will be describing the MC simulated background samples.

Diboson

The samples in this category refer to the weak boson pair production WW , ZZ or WZ associated with additional jets. Five different samples are present in this category, all containing at least two prompt leptons. Samples describing the decay of Dibosons into fully hadronic final states are not considered. Two of them contain semileptonic decays

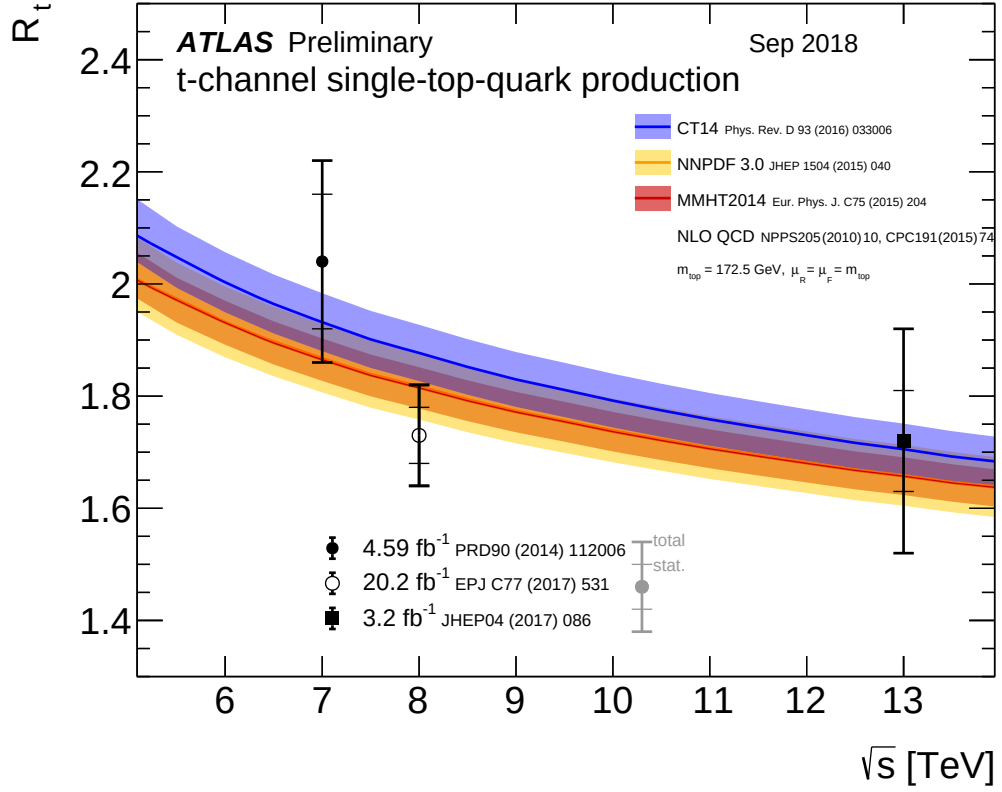


Figure 4.2: Summary of the ATLAS measurements of R_t , the ratio of the t-channel top-quark production cross-section to the t-channel anti-top-quark production cross-section. The measurements are compared to NLO QCD calculations using the CT14, NNPDF 3.0 and MMHT2014 PDF sets [70].

of the Diboson pair, which are $Z(\rightarrow \ell^+\ell^-)Z(\rightarrow q\bar{q})$ and $Z(\rightarrow \ell^+\ell^-)W(\rightarrow q\bar{q})$. The remaining three instead are fully leptonic decays: $ZZ \rightarrow \ell^+\ell^-\ell^+\ell^-$, $ZW \rightarrow \ell^+\ell^-\ell\nu$ and $WW \rightarrow \ell\nu\ell\nu$. The semileptonic ones, alongside with the fully leptonic WW , comprise the reducible backgrounds, because they pass the trilepton selection due to a fake or non-prompt lepton. The ZZ sample is also reducible, because it has four prompt leptons instead of the three requested, whereas the WZ sample has an identical final state with respect to tZq , because it has three prompt leptons, one neutrino, therefore having missing energy, and additional jets.

The requirements are for the invariant mass of the Opposite Sign Same Flavour (OSSF) lepton pair invariant mass $m_{\ell^+\ell^-}^{\text{OSSF}} > 4 \text{ GeV}$ and the momentum of the two leptons with higher invariant mass to be greater than 5 GeV.

The events were simulated using both SHERPA2.2.1 and SHERPA2.2.2 generator [71], including off-shell and Higgs boson contributions. The final states were generated using matrix elements either at LO or NLO in QCD, depending on the number of additional partons added. For PDFs, the NNPDF3.0NNLO set was used, whereas virtual QCD corrections were provided by the OPENLOOPS library [72–74].

$t\bar{t}Z$

Five different samples make up for this category, depending on the decay of the Z boson: ee , $\mu\mu$, $\tau\tau$, $\nu\nu$ and finally the fully hadronic $q\bar{q}$. Also non-resonant OSSF lepton pair with $m_{\ell\ell} > 5$ GeV are considered. All the samples are inclusive in the top decay. Therefore, the W boson can decay either leptonically or hadronically. The $Z \rightarrow q\bar{q}$ samples are part of the reducible backgrounds, whereas the $Z \rightarrow \ell\ell$ samples can be irreducible backgrounds if either top or $antitop$ decay leptonically.

The events were generated using the MADGRAPH5_AMC@NLO2.8.1 generator at NLO in α_S using the NNPDF3.0NLO PDF set, same as the signal. Likewise, events were interfaced with PYTHIA8.244 for parton shower and hadronization, using the A14 tune and the NNPDF2.3LO PDF set.

$t\bar{t}W$

There is only one sample for the $t\bar{t}W$ process, which is inclusive in all three W bosons. Therefore, all possible final states include $3\ell 3\nu$, $2\ell 2\nu 2j$, $\ell\nu 4j$, with the addition of 2 b -jets, as can be seen in an example Feynman diagram in Figure 2.6.

The events were generated using the same specifics as the $t\bar{t}Z$ sample.

tWZ

For this sample we include leptonic decays of the Z boson alongside inclusive decays of top and W boson, thus allowing for $\ell^+\ell^-2\ell 2\nu$, $\ell^+\ell^-\ell\nu 2j$ and $\ell^+\ell^-4j$ final states.

For the generation, the same specifics of the signal sample were used.

$t\bar{t}H$

For the top quarks pair in association with a Higgs boson three different samples were used, all inclusive in Higgs boson decay, split based on the $t\bar{t}$ decay. Therefore, possible final states include $2\ell 2\nu$, $\ell\nu 2j$ and $4j$, alongside 2 b -jets and a Higgs boson.

The production of $t\bar{t}H$ events was modelled using the POWHEGBOX v2 [75–79] generator at NLO with the NNPDF3.0NLO PDF set, and the events were interfaced to PYTHIA8.230 using the A14 tune and the NNPDF2.3LOPDF set.

4 tops

For the four top quark production ($t\bar{t}t\bar{t}$) only one sample was used, inclusive in the W boson decay.

The sample was simulated at NLO using the MADGRAPH5_AMC@NLO2.3.3 generator interfaced to PYTHIA8.230 with the A14 tune and the NNPDF3.1NLO PDF set.

3 tops

For three top quarks ($t\bar{t}t$ or $t\bar{t}\bar{t}$) production there is only one sample, inclusive in the W bosons decay. The final state has 3 b -jets and either $3\ell 3\nu$, $2\ell 2\nu 2j$, $\ell\nu 4j$ or $6j$. The generation of this sample follows the same specific as 4 tops.

$t\bar{t}$

This sample belongs to the reducible background, because it includes only dileptonic decays of the $t\bar{t}$ pair, thus having a $2\ell 2\nu$ plus two b -jets final state. This sample, alongside Z +jets, comprise the *Fake* lepton background, also called *Fakes* in this thesis. The name comes from the fact that, since this sample has a dilepton final state, the selection is passed only thanks to a non-prompt lepton, which is a lepton generated inside a jet, or to a jet misidentified as a lepton (jet-faking-lepton).

The $t\bar{t}$ sample is modelled using the POWHEGBOXv2 generator at NLO with the NNPDF3.0NLO PDF set and the h_{damp} ⁹ parameter set to $1.5 m_t$. The events were then interfaced to PYTHIA8.320 with the A14 tune and the NNPDF3.1NLO PDF set.

Z +jets

Similarly to $t\bar{t}$, also Z +jets is part of the fake lepton background. The samples includes leptonic decays of the Z boson ($Z \rightarrow \ell^+ \ell^-$), with electrons, muons and taus all included. Additional non resonant lepton pair are included, provided the invariant mass $m_{\ell\ell}$ is greater then 40 GeV. Alongside the lepton pair, hadronic jets are also generated, with these jets being the ones which generate the non-prompt lepton, therefore allowing it to pass the trilepton selection.

The sample was generated with the SHERPAv2.2.1 using NLO matrix elements for up to two partons, and LO matrix elements for up to four partons using the OPENLOOPS library. The NNPDF3.0NNLO PDF set was used and the samples were normalised to the NNLO prediction [80].

4.4 Object reconstruction

This section is dedicated to the object reconstruction process works at the ATLAS experiment, with an interest only in particles that are interesting for this thesis.

Primary vertex

The primary vertex [81] of the interaction, which is the vertex in which hard scattering occurs, is selected as the pp vertex candidate with the highest sum of the p_T^2 of all associated

⁹The h_{damp} parameter is a resummation damping factor and one of the parameters that controls the matching of Powheg matrix elements to the parton shower and thus effectively regulates the high- p_T radiation against which the $t\bar{t}$ system recoils

tracks with $p_T > 500$ MeV.

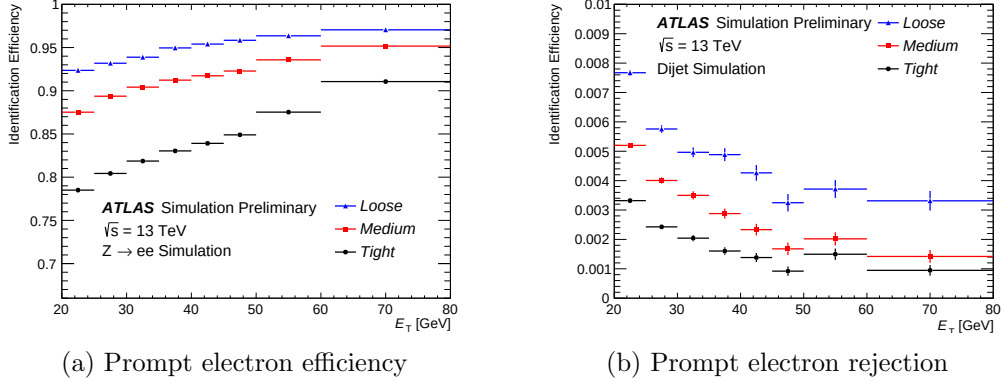


Figure 4.3: The efficiency to identify prompt electrons (left) and to misidentify hadrons as electrons, also referred to as efficiency of rejecting prompt leptons (right), for the three different IDWPs [82]

Electrons

Electrons are reconstructed when a match is found between energy deposits in the electromagnetic calorimeter and tracks in the ID [83]. Because the reconstruction requires tracks in the ID, electrons are reconstructed only in the central region of the ATLAS detector, that is $|\eta| < 2.47$, leaving out the region between the barrel and the end-caps of the ECAL ($1.37 < |\eta| < 1.52$). An additional requirement is that $E_T^{10} > 10$ GeV.

Electrons are then identified by different sets of likelihood-based identification criteria, referred to as **Tight**, **Medium** and **Loose** working points, whose specifics can be found in Figure 4.3. These three working points (WP) have a 95%, 90% and 85% efficiency [84] of identifying a prompt lepton respectively, with efficiencies measured from Z or J/ψ decays ($Z \rightarrow ee$, $J/\psi \rightarrow ee$). For the identification, multiple discrimination variables are used, such as hadronic leakage, number of hits in the pixel detector, $\Delta\eta$ between cluster position in the strip layer and the track and later shower width, accounting for all the different steps in which reconstruction is made. Common to all three WPs is the requirement of being selected by at least one of the two ECAL triggers, having a threshold on electromagnetic energy deposit of 24 or 60 GeV respectively, with a match to a track which passes isolation and shape criteria.

For this analysis the **Medium** Identification working point was used. It requires at least two hits in the ID, with one coming from the IBL, and seven total hits in the pixel and silicon-strip detectors combined. The hit in the IBL was added for better rejection of photon conversion background, that is an electron from $\gamma \rightarrow ee$ which gets misidentified as a prompt electron from the primary vertex.

For the isolation, the **PLVLoose** WP was used. Isolation is an essential property used to distinguish prompt and fake leptons. As aforementioned, prompt leptons are the ones

¹⁰ $E_T = E \sin \theta$

coming from the decay of W or Z bosons, whereas fake leptons are the ones generated inside a jet or are *jet-faking-lepton*. Therefore, when a prompt lepton is generated, it usually does not have additional tracks nearby, whereas a fake lepton is found with many tracks around it. This can be seen in Figure 4.4. Consequently, isolation WPs (IWP) have been implemented with the goal of identifying a prompt lepton by analysing its surroundings. The IWP used for this analysis evaluates the isolation using two separate algorithms.

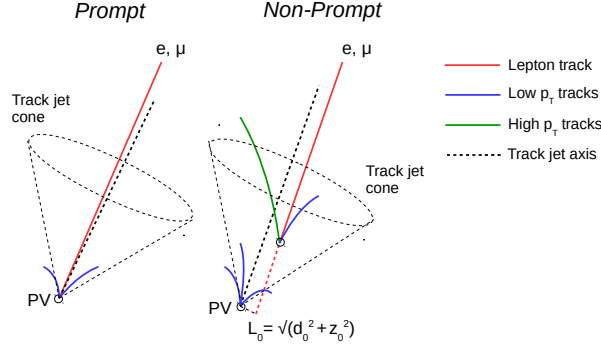


Figure 4.4: A scheme showcasing the difference between a prompt and a non-prompt (fake) lepton.

The first one is based merely on the tracks inside a cone centred on the lepton track. The algorithm counts the p_T of all the tracks within a cone with a variable radius, decreasing at higher energies. The lepton is then considered isolated if the ratio between the sum of all the transverse momentum tracks inside the cone and the lepton p_T ($\sum p_T^{\text{cone}} / p_T^\ell$) is lower than a given threshold. Since a prompt lepton has few and low-energy tracks around it, the ratio is very small, resulting in it not overcoming the threshold. On the other hand, for fake leptons p_T^{cone} takes a non-negligible value, since many high p_T jets can be found inside the cone. Therefore, the lepton does overcome the threshold, and is therefore identified as fake.

Additionally, the **PLVLoose** WP uses the *Prompt Lepton Veto* algorithm to identify prompt leptons. This algorithm uses a Multi Variate Analysis (MVA) to evaluate whether a lepton is prompt or not. The MVA uses, alongside the ratio defined earlier, additional variables for the training, such as the number of tracks in the cone, the distance ΔR between lepton track and jet-track axis, the ratio between p_T^ℓ and $p_T^{\text{track-jet axis}}$ and other variables bringing information on the shape of the calorimeter cluster generated. Therefore, the **PLVLoose** WP is able to perform the isolation with a higher rejection than WPs which do not make use of the *Prompt Lepton Veto* MVA. This comparison can be seen in Figure 4.5, where it is showcased how the PLV WPs have the highest efficiency of selecting prompt leptons, as well as a better rejection of fake leptons than **FCTight** and **PFlow**. The **PLVLoose** WP, which is the one in the analysis, has a higher efficiency of reconstructing prompt electron than **PLVTight** (85% vs 65% for $p_T = 15$ GeV), whose efficiency is

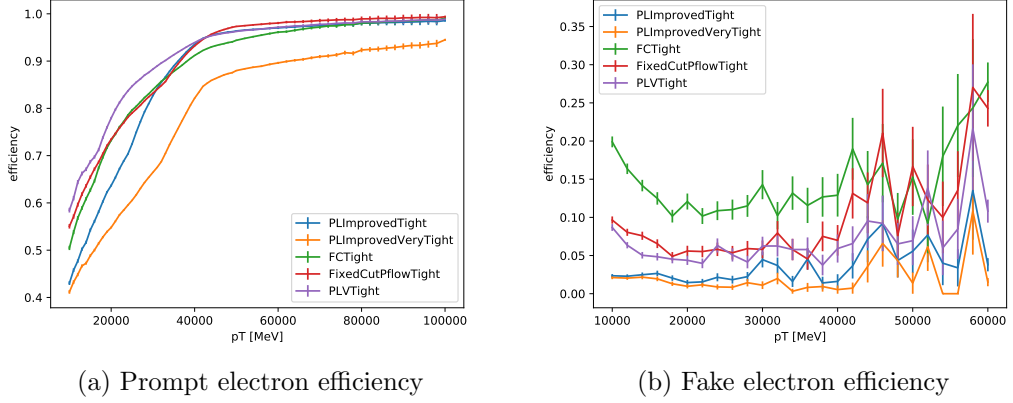


Figure 4.5: Efficiency for identifying prompt (left) and fake (right) electrons at different values of p_T for different IWP. The one used in this analysis is represented in purple.

displayed in purple in Figure 4.5, at the cost of a lower rejection for non-prompt lepton, which is twice as much especially at low- p_T (10% vs 5% at $p_T = 15$ GeV). Therefore, more fake electrons will pass the selection. The previous analysis [46] used the **Gradient** IWP, a WP which used only the track information and not the *Prompt Lepton Veto* MVA.

Muons

There are four different types of muons that are reconstructed at the ATLAS detector:

- **Combined Muons (CB)**: reconstructed from the matching of ID tracks with a MS track
- **Segment-Tagged Muons (ST)**: reconstructed from a combination of ID tracks and at least one local track in the muons chambers
- **Stand-Alone Muons (SA)**: reconstructed from the MS only
- **Calorimeter-Tagged Muons (CT)**: reconstructed from tracks in the ID which match an energy deposit in the ECAL compatible with a minimum ionising particle

Similarly to electrons, three different IDWPs are implemented, **Loose**, **Medium** and **Tight**. For this analysis the **Medium** WP was used, whose specifics are showcased in Figure 4.6. This IDWP uses only CB and SA muons, minimising the systematics uncertainties associated with muon reconstruction and calibration. For SA muons the requirement is to have at least three hits in each of the three layers of the muon chambers only in the $2.5 < |\eta| < 2.7$ region, whereas CB muons must have at least 3 hits in the chambers and must satisfy a loose selection on the compatibility between ID and MS momentum measurements, so as to suppress contamination due to hadrons-faking-muons. As Figure 4.6(a) displays, muon identification is easier than it is for electrons, as the efficiency for prompt muons is greater than 97% over the 7 – 100 GeV range for p_T , with a background rejection

always lower than 98%. Likewise, the efficiency as a function of η is $> 99\%$ everywhere except in the central region $|\eta| < 0.1$, where it drops to 60%.

Same as the electrons, the **PLVLoose** WP was used for the isolation, whereas the previous analysis [46] used the **Gradient** IWP. The efficiencies for accepting prompt muons and rejecting fake muons are similar to the ones for the electrons. Consequently, more fake muons will pass the selection as well.

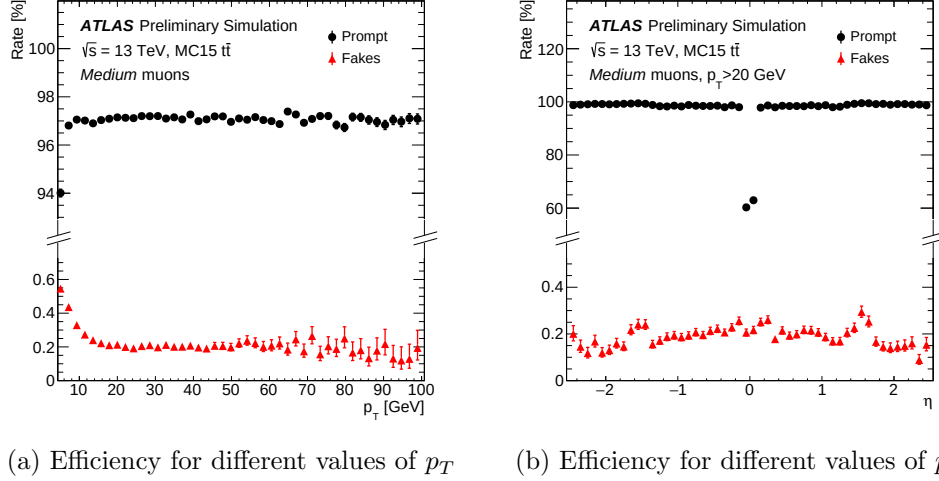


Figure 4.6: Efficiency of identifying prompt (black) and fake (red) muons for the **Medium** IDWP, as a function of p_T (left) and η (right) [85].

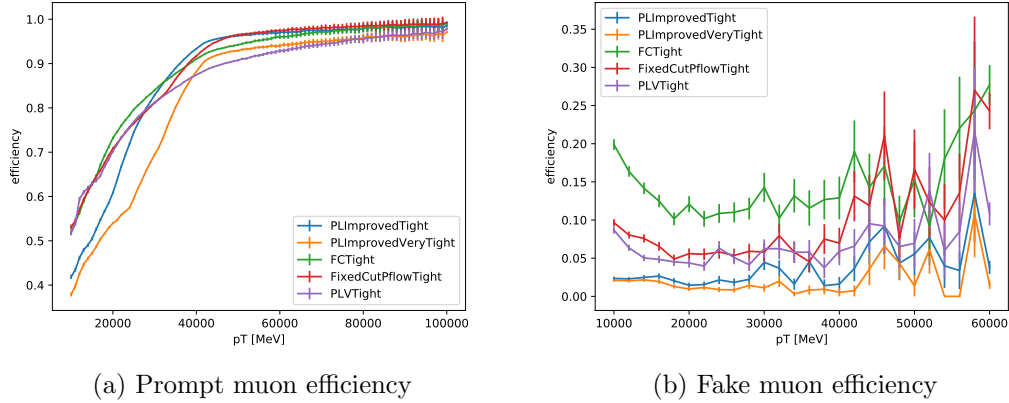


Figure 4.7: Efficiency for identifying prompt (left) and fake (right) muons at different values of p_T for different IWP. The one used in this analysis is represented in purple.

Jets

When a quark or a gluon is produced in the final state of a process, hadronization happens. This refers to the formation of a hadron shower, due to the strong interaction increasing

with the distance. This process is non-perturbative, and cannot therefore be computed with perturbative QCD, as it is the case for the hard scattering and the FS corrections. As a result of hadronization, chunks of collimated particles emerge from the parton shower, also called *hadronic jets* or, simply, *jets*.

Jet reconstruction is essential in ATLAS analyses, because of the LHC being a hadron machine. Therefore, it is important to have an algorithm that clusters the observed particles in jets, starting with energy deposits in the HadCAL.

The reconstruction process starts from grouping together energy deposits in adjacent cells of the calorimeter, thus generating a *topocluster*. Topoclusters are then formed by a growing-volume algorithm, which starts from a calorimeter cell with a highly significant seed signal. In order to control the cluster formation, the cell significance ζ_{cell}^{EM} as in Equation (4.4.1), where $\sigma_{noise,cell}^{EM} = \sqrt{(\sigma_{noise,cell}^{electronic})^2 + (\sigma_{noise,cell}^{pile-up})^2}$.

$$\zeta_{cell}^{EM} = \frac{E_{cell}^{EM}}{\sigma_{noise,cell}^{EM}} \quad (4.4.1)$$

Seeding, growth and boundary features of the topoclusters are defined by three parameters, S , N and P respectively. Thresholds in terms of $\sigma_{noise,cell}^{EM}$ are then defined (Equation (4.4.2)) using these three parameters, consequently applying selections based on $\zeta_{noise,cell}^{EM}$.

$$\begin{cases} |E_{cell}^{EM}| > S\sigma_{noise,cell}^{EM} & \implies |\zeta_{cell}^{EM}| > S \text{ (default } S = 4); \\ |E_{cell}^{EM}| > N\sigma_{noise,cell}^{EM} & \implies |\zeta_{cell}^{EM}| > N \text{ (default } N = 2); \\ |E_{cell}^{EM}| > P\sigma_{noise,cell}^{EM} & \implies |\zeta_{cell}^{EM}| > P \text{ (default } P = 0). \end{cases} \quad (4.4.2)$$

Cells adjacent to the seed are selected in the topocluster only if their ζ_{cell}^{EM} is greater than the thresholds defined in Equation (4.4.2), and the total energy of the topocluster is the sum of the energy deposits of all cells belonging to the topocluster.

The radius of a topocluster is a parameter R , chosen in advance. Two clusters are grouped when their distance $\Delta R_{i,j}$ is lesser than R , with the distance defined in terms of the rapidity Y and the azimuthal angle ϕ as $\Delta R_{i,j}^2 = (Y_i - Y_j)^2 + (\phi_i - \phi_j)^2$.

The jet algorithm works in an iterative way. Firstly, the variables $d_i = \left(k_T^{(i)}\right)^{2p}$ and $d_{i,j} = \min \left[\left(k_T^{(i)}\right)^{2p}; \left(k_T^{(j)}\right)^{2p} \right] \frac{\Delta R_{i,j}^2}{R^2}$ are computed. From this list, the variable $d_{\min} = \min(\{d_i\} \cup \{d_{i,j}\})$ is extracted. If in the list there is an object i such that $d_{\min} \equiv d_i$, then i is defined as a jet and removed from the list. Otherwise, there must be a pair (i, j) such that $d_{\min} \equiv d_{i,j}$. In this latter case, the objects i and j are merged into one object $m \neq i, j$, whose four-momentum k_m is the sum of k_i and k_j . The objects are then removed from the list, and the process is reiterated until only jets are found.

The exponent p in the definitions of d_i and $d_{i,j}$ separates the different algorithms: $p = 1$ is the k_T algorithm, $p = 0$ is the Cambridge-Aachen algorithm and $p = -1$ is the

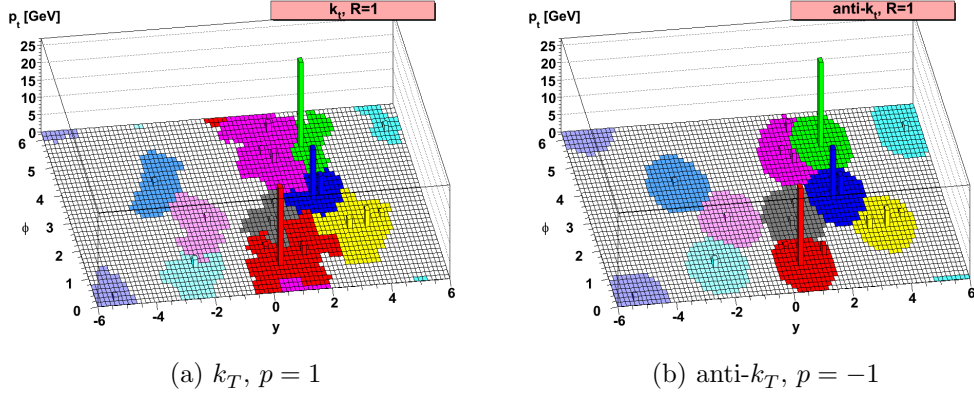


Figure 4.8: A sample parton-level event with many random soft “ghosts”, clustered with the k_T (left) and the anti- k_T (right) algorithms [86].

anti- k_T algorithm. The latter is the one used in ATLAS.

The anti- k_T algorithm defines $d_i = \frac{1}{(k_T^{(i)})^2}$ and $d_{i,j} = \min \left[\frac{1}{(k_T^{(i)})^2}; \frac{1}{(k_T^{(j)})^2} \right] \frac{\Delta R_{i,j}^2}{R^2}$. A visualisation of the difference between the k_T and the anti- k_T algorithms can be seen in Figure 4.8. The anti- k_T algorithm starts the seed by the hardest objects, in contrast with the k_T algorithm, and subsequently groups closeby objects to hardest objects. The jets generated have a perfect conical shape with radius R , and are insensitive to substructures.

In this analysis, jets are clustered with the anti- k_T algorithm with $R = 0.4$. The requirement on the jet p_T has been changed throughout the analysis, while different event selection were tested, whereas in all selections jets were required to have $|\eta| < 4.5$. In order to reject forward jets originating by additional pp interactions, a forward jet vertex tagger (fJVT) has also been implemented. This tagger works as follows: once the hard vertex scattering is identified, the *jet vertex fraction* is computed as in Equation (4.4.3), and the jet is rejected if JVF is lower than a given threshold. For this analysis, the fJVT Medium WP was used, which has a 97% efficiency of selecting hard scattered jets and a pile-up efficiency close to 54% for jets with $40 \text{ GeV} < p_T < 50 \text{ GeV}$.

$$JVF = \frac{\sum_{\text{hard scattering track}} p_T^{\text{track}}}{\sum_{\text{track}} p_T^{\text{track}}} \quad (4.4.3)$$

b -jets

b -jets are jets generated from a *bottom* quark. They are of extremely importance in any *top* quark analysis, because the branching ratio of *top* decay $t \rightarrow Wb$ is 1. Therefore, every time a *top* quark is produced, a b -jet is generated too. Consequently, it is essential to correctly identify b -jets.

b -jets differ from other hadronic jets because b -hadrons have a longer life-time ($\tau \simeq$

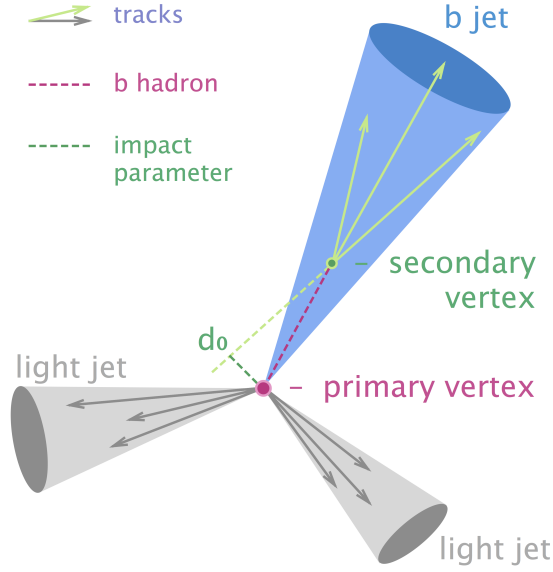


Figure 4.9: Schematic view of a b -hadron decay inside a jet coming from a secondary vertex, compared to light jets.

10^{-12} s) than c - and light-quark hadrons. Therefore, the b -jet has longer mean decay length, which leads to measurably secondary vertices and impact parameters of the decay products, as showcased in Figure 4.9.

b -jets identification is based on several objects reconstructed in the ATLAS detector, mainly tracks, vertices and the jet flavour label. The b -tagging algorithm considers only tracks with $p_T > 500$ MeV, with an efficiency ranging from 91% in the central region ($|\eta| < 0.1$) to 73% in the forward region ($2.3 < |\eta| < 2.5$). Since track reconstruction happens in the ID, b -jets must have $|\eta| < 2.5$.

The algorithm for b -jets identification is called DL1R [87]. Pseudo-continuous b -tagging WPs are used, with different values for b -jet efficiency and c , τ and light jets rejection shown in Table 4.3. For this thesis, both the `eff_70` and `eff_85` WPs were used.

Additionally, a flavour label is assigned to all simulated jets. Jets are labelled as b -jets if, within a cone of $\Delta R = 0.3$ around the jet axis, they are matched to at least one weakly decaying b -hadron with p_T greater than 5 GeV. When this is not the case, a c -hadron or τ are searched, and, if found, labelled. Otherwise, the jet is labelled as a light jet.

Missing energy

Neutrinos are particles which do not interact with any of the detectors. Therefore, they can be reconstructed only using thanks to the momentum conservation law. Since the initial state transverse momentum is zero, the final state one has to be zero too. Subsequently, candidate neutrinos are defined by missing transverse energy E_T^{miss} , whose definition can be found in Equation (4.4.4), where the two components E_x^{miss} and E_y^{miss} are calculated

Name	b -jet efficiency (%)	c -jet R	light-jet R	τ -jet R
eff_60	60.61	27	1495	314
eff_70	70.56	9	429	61
eff_77	77.50	4	141	17
eff_85	85.39	2	31	4

Table 4.3: Efficiency for b -jet reconstruction and rejection (R) corresponding to different b -tagging efficiency single-cut operating points for the DL1r algorithm, evaluated on $t\bar{t}$ events [88].

as the magnitude of the negative vector sum of the transverse momentum of all jets with $p_T > 20$ GeV, all leptons with $p_T > 25$ GeV and a soft term built from tracks that are associated to the hard-scatter vertex, which are not associated to any of the reconstructed objects.

$$E_T^{miss} = \sqrt{(E_x^{miss})^2 + (E_y^{miss})^2} \quad (4.4.4)$$

4.5 Event selection

This thesis focuses on the cross section measurement of the tZq process using the trilepton final state. This state consists of three charged leptons (only e or μ , hadronic τ are not considered), of which two come from the Z boson and one from the W boson, one neutrino, at least one b -quark, which generates a b -jet, and at least one light quark. Example final states can be seen in Figures 2.7 to 2.9. Because the leptonic decay is the one with the lowest branching ratio (BR) for both Z ($BR(Z \rightarrow ee) \simeq BR(Z \rightarrow \mu\mu) \simeq 3.36\%$) and W ($BR(W \rightarrow e\nu_e) \simeq BR(W \rightarrow \mu\nu_\mu) \simeq 10.65\%$) bosons, this final state is the least likely to happen for tZq production, with $BR(ZW \rightarrow \ell^+\ell^-\ell\nu) \simeq 1.76\%$, including also $Z \rightarrow \tau\tau \rightarrow \ell\ell 4\nu$ and $W \rightarrow \tau\nu \rightarrow \ell 4\nu$. In spite of that, this final state has been chosen because it is purer than the other channels with a higher BR, because of the presence of leptons. For comparison, the final state with the highest BR is the full hadronic final state ($Z \rightarrow q\bar{q}$, $W \rightarrow q\bar{q}$), with a BR of 0.48, but the absence of leptons makes it much more difficult to handle.

The most important background processes for this thesis are $t\bar{t}Z$, Diboson+jets (mostly due to WZ), Fakes leptons ($t\bar{t}$ and Z +jets) and other small contributions from $t\bar{t}W$, $t\bar{t}H$, tWZ and 3 and 4 tops processes.

The Z boson and the top quark must be reconstructed in order to differentiate the signal from some of the backgrounds. For instance, the Z boson mass distribution, built from the invariant mass of the lepton pair $m_{\ell\ell}$ can help discriminate this process from other processes where a Z boson is not present. A summary of all symbols representing the reconstructing objects is presented in Table 4.4. The object are reconstructed as follows: the two leptons coming from the Z boson, ℓ_i^Z , are the two opposite-sign same flavour leptons whose invariant mass is closer to m_Z . Consequently, the lepton coming

Symbol	Description
ℓ_1^Z	Highest- p_T lepton from the reconstructed Z boson
ℓ_2^Z	Lowest- p_T lepton from the reconstructed Z boson
ℓ_W	Lepton from the reconstructed W boson from the t -quark decay
Z	Reconstructed Z boson
W	Reconstructed W boson
b_j	Highest- p_T b -tagged jet
j_f	Forward jet
j_r	Radiation jet
$\ell_{1,2,3}$	p_T -ordered leptons
$j_{1,2,3}$	p_T -ordered jets

Table 4.4: Summary on object reconstruction

from the W boson decay (ℓ_W) is the lepton whose invariant mass with the other two differs more from the Z boson mass. The forward jet is the non- b -jet with the highest invariant mass with the heaviest b -jet, whereas the radiation jet j_r is the highest- p_T non-forward and non- b -jet.

In this analysis multiple event selections were tested, aiming at finding the one which gave the cross section measurement with the lowest uncertainty. Table 4.5 displays the three selections I will present in this analysis.

Common to all the selections is the requirement to have exactly three tight leptons, not including hadronically-decaying τ , two of which must form an Opposite Sign Same Flavour (OSSF) pair. The OSSF requirement is used to enhance the Z boson with respect to other backgrounds in which the Z boson is not present, because in a $Z \rightarrow \ell\ell$ decay, the two leptons have the same flavour and are opposite-signed. Therefore, final state combinations are $ee\mu$, $\mu\mu e$, eee and $\mu\mu\mu$. In the first two cases the OSSF lepton pair is evident, whereas when three same flavour leptons are present, the OSSF pair is made by the two opposite sign leptons whose invariant mass is closer to the Z boson mass. Additionally, a 10 GeV cut is applied on $|m_{\ell\ell} - m_Z|$, in order to reduce the non-resonant contribution (Figure 2.9).

The first selection (**Default**) is the one which is more similar to the old analysis. It uses tight cuts on the leptons p_T , in order to reduce the Fakes contribution, because the PLVLoose IWP has a lower rejection at low- p_T . The b -tagging WP chosen has a 70% efficiency, meaning also a good rejection of c - and light-jets, as Table 4.3 displays, and the threshold for jets p_T is set at 35 GeV. The **Loose** selection is, as the name suggests, looser in its definition. Lepton p_T thresholds have been lowered down to 15 and 10 GeV for the second and third lepton, which results in an increase in the Fakes due to the lower fakes rejection at low- p_T . Additionally, the b -tagging WP was chosen with a 85% efficiency, hence having a very low rejection of c - and light-jets. Therefore, the Diboson contribution increases as well. Moreover, the p_T of the jets has to be greater than 20 GeV. Finally, the **Medium** selection is a bit tighter than **Loose** because it has a tighter cut on the jets' p_T , set

at 25 GeV. Additionally, for this selection also events with 5 jets were included, whereas the previous two selections have only 2 to 4 jets, with 1 or 2 b -jets, with the exception of the $2j2b$ region.

Each event carries a statistically independent weight ω_i , $i = 1, \dots, n$. This weight takes into account the cross-section of the process, the integrated luminosity and all the MC/data correction factors from object identification, isolation and trigger requirements. The event yields are evaluated as $\mu = \sum_{i=1}^n \omega_i$ and the statistical uncertainty σ_μ is defined as $\sigma_\mu = \sqrt{\sum_{i=1}^n \omega_i^2}$ [89].

Event yields for the different selections are reported in Table 4.5, alongside the signal significance $S/\sqrt{S+B}$ and $S/\sqrt{B}$. From these yields we can see the differences between the three selection. The **Default** selection is the purest one for the signal, with a tZq contribution of 19.9%. The Fakes account for little less than 10%, $t\bar{t}Z$ makes up for 40% and finally Diboson events, here split based on the jet flavour, are 21% of the total. The signal significance is the higher among the regions, at 6.52.

The **Loose** selection instead, in spite of having 70 signal events more than **Default**, has a much lower signal contribution. This is due to the increase in both Fakes and Diboson, given by the lower lepton p_T threshold and higher b -tagging WP. In detail, Fakes events increased more than 5 times with respect to **Default**, going from 115 to 622, whereas Diboson's yields were increased by 6 times. In particular, Diboson+ c and light jets had the greater rise, because their rejection with the **eff_85** WP is respectively 77% and 93% less than it was for **eff_70**. Due to the large increase in these backgrounds, signal contribution and signal significance dropped to 10.7% and 5.57 respectively, marking this selection as the one with the lowest figures in both categories.

Finally, the **Medium** selection is the selection with the greater signal yields, 326.3. This is not only given by the decrease in the jet p_T threshold, but also by the inclusion of 5 jets events. The tighter jet p_T threshold results in a decrease in Diboson events, countered by a 50% growth in $t\bar{t}Z$ and a 22% increase in Fakes with respect to the **Loose** selection. Overall, this selection provides the greater statistics, with a total of 2974.9 events, 2.8 times more than **Default**. Its signal significance is 5.98, smaller than **Default** but greater than **Loose**.

Event selections for the SRs		
Exactly 3 tight leptons with $ \eta < 2.5$ (e and μ)		
≥ 1 OSSF pair		
$ m_{ll} - m_Z < 10 \text{ GeV}$		
Isolation WP for leptons: PLVLoose		
Default	Loose	Medium
$p_T(\ell_1) > 27 \text{ GeV}$	$p_T(\ell_1) > 27 \text{ GeV}$	$p_T(\ell_1) > 27 \text{ GeV}$
$p_T(\ell_2) > 20 \text{ GeV}$	$p_T(\ell_2) > 15 \text{ GeV}$	$p_T(\ell_2) > 15 \text{ GeV}$
$p_T(\ell_3) > 15 \text{ GeV}$	$p_T(\ell_3) > 10 \text{ GeV}$	$p_T(\ell_3) > 10 \text{ GeV}$
$p_T(\text{jets}) > 35 \text{ GeV}$	$p_T(\text{jets}) > 20 \text{ GeV}$	$p_T(\text{jets}) > 25 \text{ GeV}$
70% b -tagging WP	85% b -tagging WP	85% b -tagging WP
SR up to 4 jets, 2 b -jets	SR up to 4 jets, 2 b -jets	SR up to 5 jets, 2 b -jets

Table 4.5: Different selections used for this analysis.

Sample	Default		Loose		Medium	
	2-4 jets		2-4 jets		2-5 jets	
	1-2 b -jets		1-2 b -jets		1-2 b -jets	
tZq	212.6 $\pm$	7.7	291.0 $\pm$	17.2	326.3 $\pm$	11.3
$VV + b$	136.4 $\pm$	4.9	282.3 $\pm$	10.5	268.9 $\pm$	9.0
$VV + c$	79.0 $\pm$	2.9	574.2 $\pm$	21.0	524.3 $\pm$	17.2
$VV + l$	14.4 $\pm$	0.6	531.9 $\pm$	19.8	411.8 $\pm$	13.9
$t\bar{t}Z$	414.2 $\pm$	20.8	314.7 $\pm$	27.2	549.5 $\pm$	26.3
$t\bar{t}W$	14.9 $\pm$	0.6	17.8 $\pm$	0.7	21.9 $\pm$	0.8
tWZ	64.3 $\pm$	10.4	69.7 $\pm$	9.3	97.1 $\pm$	15.3
$t\bar{t}H$	12.5 $\pm$	0.4	10.8 $\pm$	0.4	17.5 $\pm$	0.6
Fakes	115.2 $\pm$	5.8	621.7 $\pm$	38.5	757.4 $\pm$	39.5
Other	0.4 $\pm$	0.0	11.5 $\pm$	1.3	0.3 $\pm$	0.0
Total	1064.2 $\pm$	41.4	2725.6 $\pm$	105.4	2974.9 $\pm$	104.4
S/B	0.25		0.12		0.12	
$S/\sqrt{B}$	7.28		5.89		6.23	
$S/\sqrt{S+B}$	6.52		5.57		5.98	

Table 4.6: Event yields for the different selections with statistical only uncertainties. The $2j2b$ region was never included in the SRs. Fakes refer to $t\bar{t}$ and Z +jets.

4.6 Analysis structure

As aforementioned, this thesis aims at providing an improved measurement of the inclusive cross section. In order to do so, different event selections with a tripton plus jets and missing energy final state, described in Section 4.5, were investigated, aiming at increasing the signal acceptance. The backgrounds can be divided into prompt and non-prompt. Prompt backgrounds are irreducible, meaning their signature in the detector is the same as the signal. These backgrounds, which all have three prompt leptons, some missing energy, and jets, of which one in the forward direction and one b -jet, include mostly $t\bar{t}Z$ and Diboson+jets, mainly WZ +jets. Non-prompt backgrounds, also labelled as Fakes, include $t\bar{t}$ and Z +jets events, in which only two prompt leptons are present. Therefore, these events pass the selection thanks to a non-prompt lepton, which is a lepton generated inside a hadronic jet. For the Diboson and the Fakes backgrounds, a data-driven estimation was carried out, as described in Chapter 5, whereas the other backgrounds are estimated by the Monte Carlo simulations.

Multiple Neural Network (NN) trainings were tested, with the goal of finding the best separation between signal and backgrounds. These NNs include Binary, in which the signal is trained versus all the backgrounds, and Multi Class, where multiple specific backgrounds are separately targeted. In this analysis, both a Multi Class with 3 classes (MC-3) and with 4 classes (MC-4) were tested. These trainings are presented in Chapter 6.

To extract the cross section, a maximum Likelihood estimator (MLE) binned fit is performed. In this analysis, a blind fit was implemented, in which real collision data is replaced by the sum of signal and background expectations from Monte Carlo. Several regions are included in the fit, both where the signal is dominant, called Signal Regions (SR), and regions devoted to the control of specific backgrounds (Control Regions, CR). These fits are described in Chapter 7.

Chapter 5

Background estimation

This chapter presents a description of the estimation of two background sources that need a special treatment: the diboson (Section 5.1) and the fake lepton (Section 5.2) backgrounds. The work that led to this chapter has been performed in parallel with the rest of the analysis. Therefore, for the specifics regarding the fit inputs is best to read through Chapter 7, where all the details regarding the systematics will be presented. This chapter will focus on the **Medium** selection (Table 4.5), but similar analyses have been done also on other selections.

5.1 Diboson background estimation

Firstly, I will describe the treatment of the diboson background VV . For the whole analysis, a flavour classification of the diboson background was implemented, thus splitting the VV contribution in three different sub-samples: $VV + b$, $VV + c$ and $VV + l$, meaning diboson plus at least one b -jet, diboson plus at least one heavy c -jet and no b -jets and diboson plus only light jets, respectively. this background has to be reweighted because it is a Diboson+jets background, and the additional jets description and multiplicity is not well described in the Monte Carlo by the SHERPA generators. As can be seen from Table 4.6, the diboson background make up for more than 45% of the total background sources. Therefore, it is essential to correctly estimate its expected yields.

5.1.1 Normalisation factor extraction

As previously stated, this sample is a diboson+jets sample, meaning additional jets have been implemented alongside the WZ , ZZ and WW production. This sample can be either a reducible or irreducible background, as it can pass the trilepton selection either with three prompt leptons, in the WZ case, or with a non-prompt lepton. Four different diboson-enhanced control regions (CR) were defined, orthogonal to the SRs. These regions have the same selections of the SRs (Table 4.5), with the exception of b -jet multiplicity, which is set to 0, thus giving the $2j0b$, $3j0b$, $4j0b$ and $5j0b$ CRs. This selection was implemented in

order to reduce the signal contribution as much as possible, since the signal has always at least one b -jet, aiming also at increasing the VV background, because, since b -jets are the heaviest hadronic jets that can be generated, they are less likely to be produced alongside a VV production than lighter jets. In these regions, the Fakes were estimated from Monte Carlo.

The CR yields are presented in Table 5.1. As expected, the signal contribution is negligible. It is clear from the table that the background normalisation is not correct, because the Data/MC agreement differs from 1 for as much as 10% in some regions. From these yields, the normalisation factor k was extracted, defined as in Equation (5.1.1), where MC_{noVV} and MC_{VV} represent the non-diboson and the diboson contribution in the Monte Carlo simulated samples respectively. Since there is no theoretical reason for the jet flavour to influence the scaling factor, we extracted only one factor for all three diboson samples.

$$k = \frac{\text{Data} - MC_{noVV}}{MC_{VV}} \quad (5.1.1)$$

In Figure 5.1 a comparison between Data and MC is displayed as a function of the number of jets. The Magenta circles represent the normalisation factors k , which are reported in Table 5.2.

In order to cross-check this result, the same test have been made, this time multiplying the scale factors to the three diboson samples. The plots showing the yields before and after applying the scale factor are reported in Figure 5.2. We can see that the extracted normalisation factors are correct, because the right plot (Figure 5.2(b)) shows a Data/MC ratio of 1.

Sample	CR $2j0b$	CR $3j0b$	CR $4j0b$	CR $5j0b$
tZq	40.5 ± 0.3	26.0 ± 0.3	10.5 ± 0.2	2.8 ± 0.1
$VV + b$	37.2 ± 0.7	27.2 ± 0.5	14.9 ± 0.3	6.7 ± 0.2
$VV + c$	468.1 ± 3.4	290.4 ± 1.6	142.8 ± 0.9	60.1 ± 0.6
$VV + l$	3752.1 ± 8.6	1629.3 ± 4.2	634.3 ± 2.2	221.3 ± 1.1
$t\bar{t}Z$	14.3 ± 0.2	21.3 ± 0.3	19.5 ± 0.3	12.0 ± 0.2
$t\bar{t}W$	1.2 ± 0.1	0.6 ± 0.1	0.4 ± 0.1	0.2 ± 0.0
tWZ	7.8 ± 0.1	8.4 ± 0.1	5.4 ± 0.0	2.5 ± 0.0
$t\bar{t}H$	0.4 ± 0.0	0.6 ± 0.0	0.4 ± 0.0	0.3 ± 0.0
Fakes	949.1 ± 65.6	360.6 ± 30.5	95.9 ± 18.8	32.8 ± 5.1
Other	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
Total	5270.8 ± 66.3	2364.5 ± 30.8	924.3 ± 18.9	338.8 ± 5.3
Data	5710	2317	888	305
Data/MC	1.08	0.98	0.96	0.90

Table 5.1: Event yields for the four different diboson CRs.

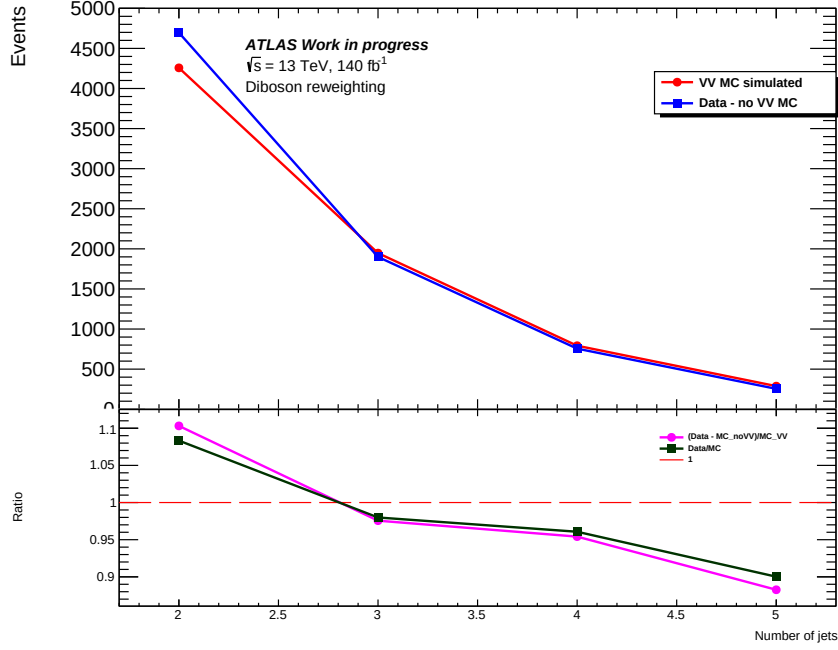


Figure 5.1: Plot displaying the comparison between Data and MC as a function of the number of jets.

	CR $2j0b$	CR $3j0b$	CR $4j0b$	CR $5j0b$
k	1.103	0.976	0.954	0.883

Table 5.2: Normalisation factors for the four CRs.

5.1.2 Validation

Nevertheless, we cannot be sure that the normalisation factors extracted can be used correctly for our analysis, because they were extracted in the $0b$ -jet regions. Therefore, two fits were performed, unblinding VV -enriched regions in order to verify if the scale factors improve the Data/MC agreement also in the $1b$ and $2b$ -regions. The details of these two fits will be presented later on in Chapter 7, whereas here I will simply focus on the Data/MC agreement in the selected CRs.

1b-jet region

For this fit, the specifics are reported in Section 7.2.3. There are 7 SRs for this fit, four with 1 b -jet and three with 2 b -jets. For the $1b$ regions, the first four bins were treated as Diboson CRs, because the signal contribution is negligible in those regions. Four additional CRs are defined for the Fakes estimation. In the 7 SRs and the 4 VV -CRs, the variable fitted is the output of the NN presented in Figure 6.24(b), whereas for the fakes CRs the fit is made to either the number of jets, in the Heavy Flavour regions, or to $p_T(\ell_3)$ in the

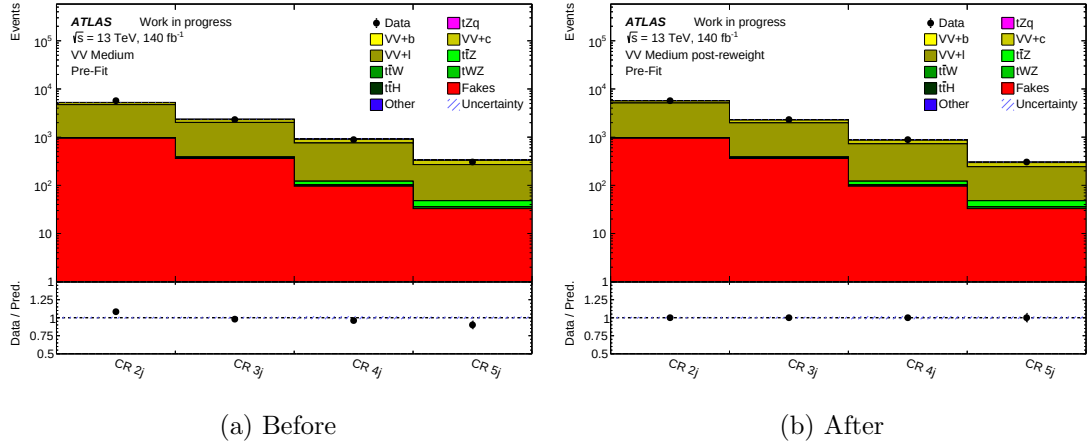


Figure 5.2: Plots showing the yields before (left) and after (right) applying the normalisation factor k to the MC.

Other regions. This fit is what is called *mixed* fit, because real data is used only in the CRs.

Two different fits were made: one applying the normalisation factors to the diboson samples, and the other one without doing so. The idea was to see whether the Data/MC agreement in those diboson-enriched regions improved with the normalisation factors. Figure 5.3 displays the post-fit yields for the two different fits, with Figure 5.4 showing in detail all the Control Regions. By looking at the χ^2 probability on the plots, it can be noted that applying the normalisation factor improves the Data/MC agreement, as the χ^2 probabilities for the fit made applying the scale factors are higher than the others.

Consequently, we were able to validate the normalisation factors for the diboson background in the $1b$ -jet region.

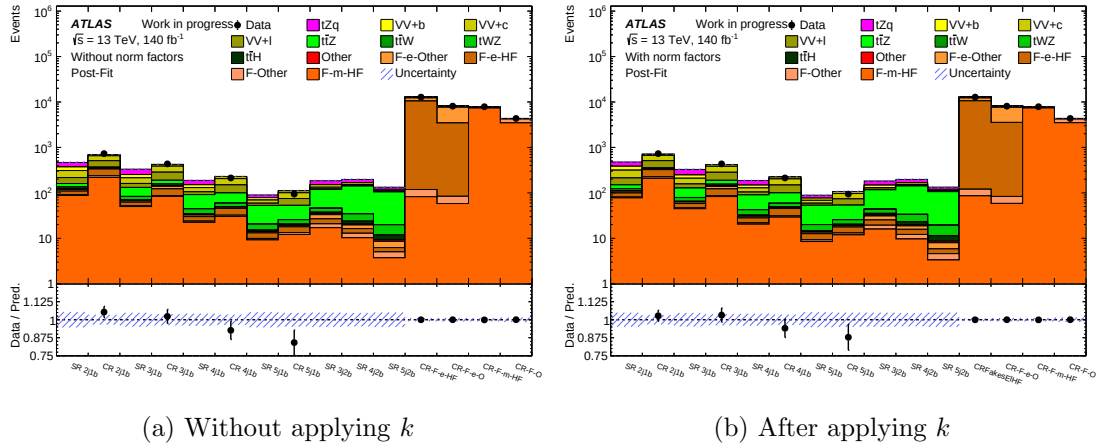


Figure 5.3: Post-fit event yield plots for all the regions, showing the comparison between the fit made without applying the normalisation factor (left) and with the normalisation factor (right).

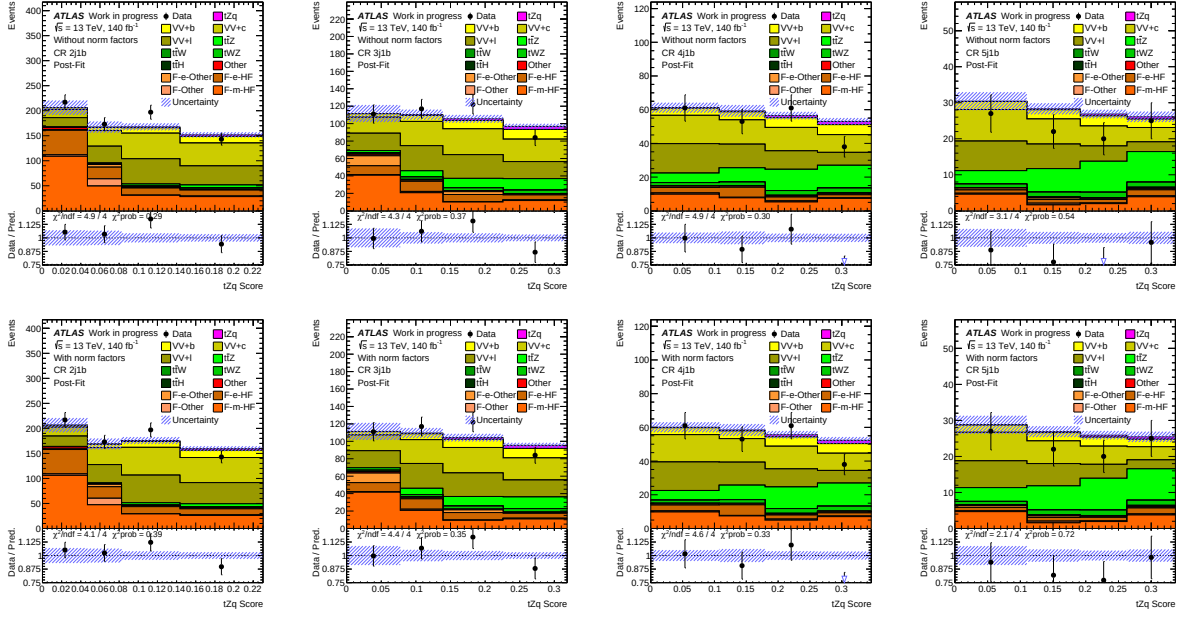


Figure 5.4: Comparison between the two fits in the diboson CRs. Top plots are taken from the fit without the normalisation factor, whereas the bottom ones are from the fit with the normalisation factors.

2b-jets region

After validating the normalisation factors in the 1b-jet region, a similar setup was made in order to validate them also in the 2b-jets region. Since the diboson sample is mostly made of 1b-jet events, the same fit setup used earlier could not be used. Therefore, the fit setup in Section 7.2.3 was used, considering only the VV 1b and the *Others* 2b CRs, alongside the four *Fakes* CRs. This way, it was possible to generate the purest diboson regions for both 1b and 2b-jets, even though the 2b-jets region is not as pure as the 1b-jet region, because the diboson contribution in the 2b-jets regions is not much. The variables fitted are NN outputs of the training presented in Section 6.4.3.

The diboson Control Region plots are displayed in Figure 5.6, and in Figure 5.5 the post-fit event yield plots are presented. Using once again the χ^2 probability to compare the two fits, we were able to say that the fit made applying the normalisation factors has a better Data/MC agreement.

Conclusion

In conclusion, the diboson normalisation factors extracted in the 0 b-jet regions were validate in both the 1b and the 2b regions, since the Data/MC agreement showed an improvement in the fits with the normalisation factor with respect to the fits made without it. Therefore, the normalisation factor was then applied to all future fits.

5.1. DIBOSON BACKGROUND ESTIMATION

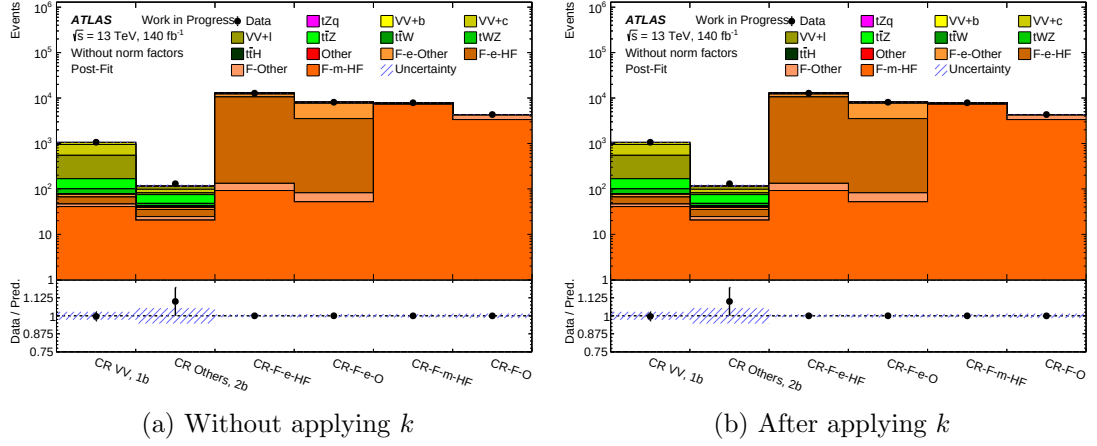


Figure 5.5: Post-fit event yield plots for all the regions, showing the comparison between the fit made without applying the normalisation factor (left) and with the normalisation factor (right).

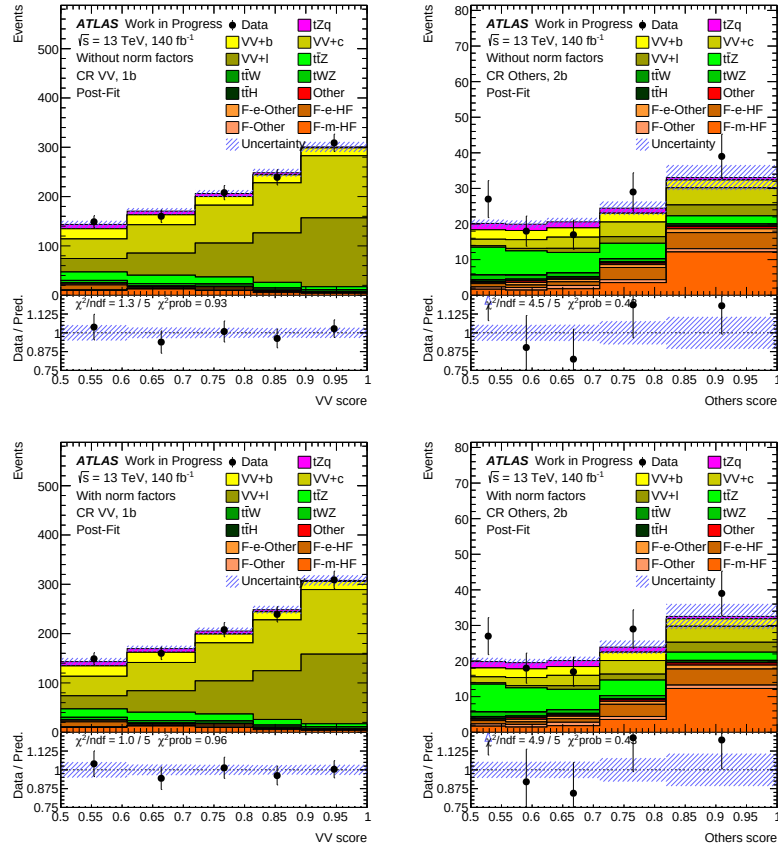


Figure 5.6: CR post-fit plots, showing the comparison between not applying (top) and applying (bottom) the normalisation factors.

5.2 Fake background estimation

The fake background is made mostly of $t\bar{t}$ and Z +jets, which are processes with two prompt leptons, and thus pass the selection with a fake lepton. Similarly to Diboson, these processes are simulated with multiple jets using the same SHERPA version, and therefore they must be reweighted to account for the generator's inaccuracy on dealing with additional jet description and multiplicity. Furthermore, the modelling of the detector response is not 100% accurate, especially for Fakes, and this approach aims at solving this inaccuracy.

In this case, four control regions were used, as described in Table 5.3. The regions differ from the SRs because they require exactly 2 tight leptons and one additional *Loose non tight* lepton, as opposed to the SRs request of exactly 3 tight leptons. Furthermore, in the HF regions the requirement is for the invariant mass of the OSSF lepton pair to be at least 10 GeV apart from the Z boson. This is due to these events coming mostly from $t\bar{t}$, which is also why there is a requirement for at least one b -jet. On the other hand, the *Others* regions require 0 b -jets, $m_T(W) > 20$ GeV, which is a region enhanced with Fakes, and a $m_{\ell\ell}$ within 10 GeV from the Z boson mass, because the events in these regions come mostly from Z +jets. The regions are divided based on the flavour (e or μ) of the loose non tight lepton, and an additional splitting between the fake lepton origin has been implemented.

For this analysis, the *Fakes* sample was split based on the origin of the fake lepton, thus generating four new samples: FAKES_{EL}_HF, FAKES_{EL}_OTHER, FAKES_{MU}_HF and FAKES_{MU}_OTHER, same as the control regions. In the HF samples, at least one fake lepton come from a heavy flavour jet, whereas in the OTHERS samples all fake leptons come from light flavour jets.

The regions were chosen because, as can be seen in Figure 5.7, they are enhanced in mostly one type of Fakes background. In particular, the two HF regions are dominated by the HF components, whereas in the two *Others* regions there is an increase in the events coming from the *Others* samples, even if the contribution to the region is not the dominant. In this way, we are able to extract four different normalisation factors, which tell us how to correct the Monte Carlo simulations so that they match real data.

The goal of this analysis was to extract the normalisation factor for each of the four samples, by doing a fit to data in the CRs. In the HF regions, the variable fitted was the number of jets, whereas in the *Other* regions the fit was made to $p_T(\ell_3)$, where ℓ_3 denotes the lowest- p_T lepton. The choice was made as these variables turned out to give the lowest uncertainties on the normalisation factors.

This fit has 4 POIs and a total of 180 nuisance parameters (NPs), divided as in Table 5.4. The $t\bar{t}$ modelling uncertainties are uncorrelated between the four regions. For the parton shower, the uncertainty was evaluated with the variation between POWHEGBOX with PYTHIA8 and POWHEGBOX with HERWIG7.21. The generator uncertainty instead was evaluated with the variation between POWHEGBOX with PYTHIA8 and MADGRAPH5_AMC@NLO with PYTHIA8, and finally the h_{damp} uncertainty was evaluated with

5.2. FAKE BACKGROUND ESTIMATION

Regions definition using Medium selection			
CR Fakes El HF	CR Fakes El Other	CR Fakes μ HF	CR Fakes Other
Exactly 2 tight leptons (e or μ)			
Loose non tight lepton is electron		Loose non tight lepton is muon	
2-5 jets			
≥ 1 b -jets	0 b -jets	≥ 1 b -jets	0 b -jets
$ m_{\ell\ell} - m_Z > 10 \text{ GeV}$	$ m_{\ell\ell} - m_Z < 10 \text{ GeV}$	$ m_{\ell\ell} - m_Z > 10 \text{ GeV}$	$ m_{\ell\ell} - m_Z < 10 \text{ GeV}$
-	$m_T(W) < 20 \text{ GeV}$	-	$m_T(W) < 20 \text{ GeV}$
Fit on number of jets	Fit on $p_T(\ell_3)$	Fit on number of jets	Fit on $p_T(\ell_3)$

Table 5.3: Definition of the four Fakes CRs.

comparison between $h_{damp} = 1.5m_{top}$ and $h_{damp} = 3m_{top}$, both generated by PYTHIA8.

Pre- and post-fit yields are presented in Tables 5.5 and 5.6, respectively, whereas Figure 5.8 displays the event distribution in the CRs, both pre (top) and post-fit (bottom). Figure 5.7 reports the pre- and post-fit yield plots for all the region, and finally in Figure 5.9 the four normalisation factors are presented. From the post-fit plots and yields, it is clear how the extracted normalisation factors are correct, because the Data/MC ratio is comparable with 1 in all the regions. The normalisation factors show that an excessive abundance of *Other* fakes was simulated, thus giving a normalisation factor of 0.62 and 0.68 for muons and electrons respectively. On the other hand, the HF component was under-estimated by 6% for both e and μ .

Overall, the normalisation factors for the heavy flavour components, which are the ones with greater contribution in the SRs, are comparable to 1.

Group	Sub-group	Nuisance Parameters
Theory	tZq	3 (PDF, PS, A14)
	$t\bar{t}Z$	3 (PDF, PS, A14)
	tWZ	2 (Norm, DR1 vs DR2)
	VV	3 (PDF, one for each flavour)
	$t\bar{t}$	12 (PS, Generator, hdamp)
Instrumental	Lepton	23
	JES	35
	JER	13
	b -tagging	85
	PileUp modelling	1
	Luminosity	1
-	-	Total = 180

Table 5.4: The list of systematics used for this fit. PS refer to *parton shower*, JES and JER are *Jet Energy Scale* and *Jet Energy Resolution*.

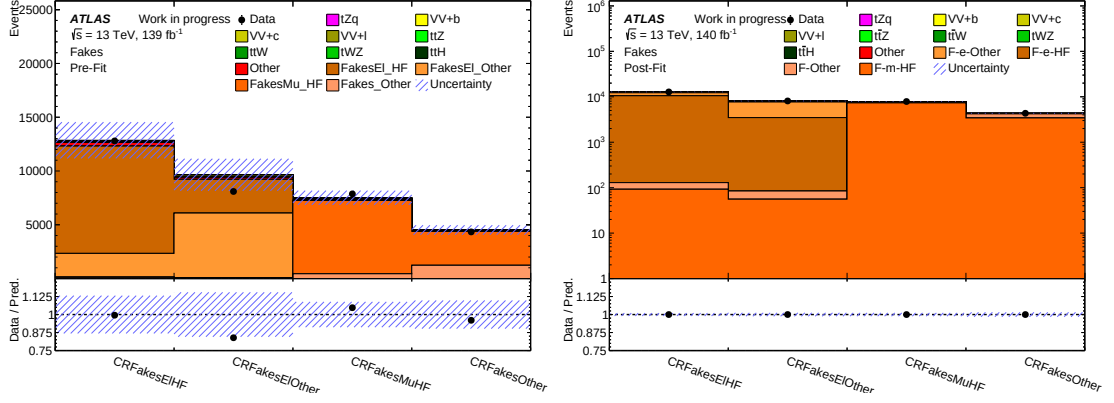


Figure 5.7: Pre- (left) and post-fit (right) event yield plot for all the fakes CRs.

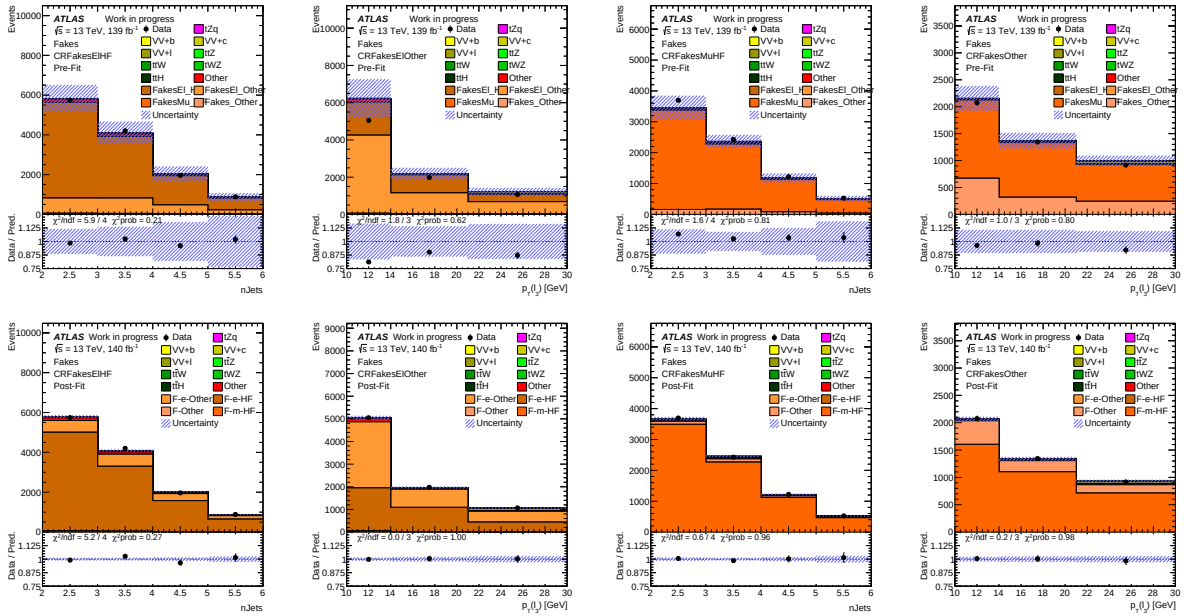


Figure 5.8: Pre- (top) and post-fit (bottom) plots in the four fake CRs.

5.2. FAKE BACKGROUND ESTIMATION

Sample	CR Fakes El HF	CR Fakes El Other	CR Fakes μ HF	CR Fakes Other
tZq	18.0 ± 2.9	2.1 ± 0.4	12.2 ± 0.6	0.9 ± 0.1
$VV + b$	22.8 ± 1.9	2.9 ± 0.4	15.3 ± 1.0	1.1 ± 0.2
$VV + c$	41.4 ± 4.5	28.8 ± 2.6	29.9 ± 2.7	12.7 ± 1.3
$VV + l$	31.4 ± 5.7	203.5 ± 21.3	23.2 ± 4.2	83.4 ± 9.2
$t\bar{t}Z$	54.0 ± 7.8	2.6 ± 0.3	34.7 ± 1.4	1.0 ± 0.2
$t\bar{t}W$	5.2 ± 0.4	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
tWZ	4.2 ± 0.6	0.8 ± 0.1	2.4 ± 0.5	0.4 ± 0.1
$t\bar{t}H$	25.0 ± 1.2	0.1 ± 0.0	12.3 ± 0.5	0.0 ± 0.0
Other	335.3 ± 71.6	179.2 ± 71.6	84.0 ± 17.2	13.5 ± 8.5
F-e-HF	9980.1 ± 1367.1	3142.0 ± 422.6	24.7 ± 3.0	6.4 ± 3.9
F-e-Other	2194.5 ± 808.8	5993.3 ± 1033.7	18.9 ± 12.9	15.6 ± 15.7
F-m-HF	84.1 ± 34.3	50.3 ± 17.6	6813.3 ± 641.0	3149.1 ± 328.4
F-Other	59.1 ± 8.3	44.5 ± 14.6	442.2 ± 55.0	1232.1 ± 140.3
Total	12855.0 ± 1685.3	9650.0 ± 1489.1	7513.1 ± 660.9	4516.3 ± 441.2
Data	12796	8096	7870	4336

Table 5.5: Pre-fit yields in the four fakes CRs.

Sample	CRFakesElHF	CRFakesElOther	CRFakesMuHF	CRFakesOther
tZq	18.0 ± 2.9	2.1 ± 0.4	12.2 ± 0.6	0.9 ± 0.1
$VV + b$	22.9 ± 1.8	3.0 ± 0.3	15.3 ± 0.9	1.1 ± 0.1
$VV + c$	41.6 ± 4.0	29.1 ± 2.4	30.1 ± 2.4	12.8 ± 1.1
$VV + l$	31.8 ± 5.0	206.2 ± 17.8	23.6 ± 3.6	84.3 ± 7.3
$t\bar{t}Z$	53.8 ± 7.6	2.6 ± 0.2	34.6 ± 1.2	1.0 ± 0.1
$t\bar{t}W$	5.2 ± 0.3	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
tWZ	4.2 ± 0.6	0.8 ± 0.1	2.4 ± 0.5	0.4 ± 0.1
$t\bar{t}H$	25.0 ± 1.1	0.1 ± 0.0	12.3 ± 0.4	0.0 ± 0.0
Other	339.3 ± 59.8	176.3 ± 61.5	83.7 ± 12.8	13.6 ± 7.1
F-e-HF	10408.0 ± 758.8	3394.9 ± 551.0	26.8 ± 5.4	6.7 ± 3.4
F-e-Other	1717.8 ± 816.7	4195.3 ± 609.5	14.7 ± 10.7	9.7 ± 7.7
F-m-HF	92.2 ± 29.5	55.7 ± 15.7	7337.6 ± 180.2	3418.5 ± 365.1
F-Other	36.7 ± 19.6	28.6 ± 15.2	277.5 ± 146.5	787.0 ± 377.7
Total	12796.6 ± 126.2	8094.7 ± 96.7	7870.8 ± 89.8	4336.2 ± 66.6
Data	12796	8096	7870	4336

Table 5.6: Post-fit yields in the four fakes CRs.

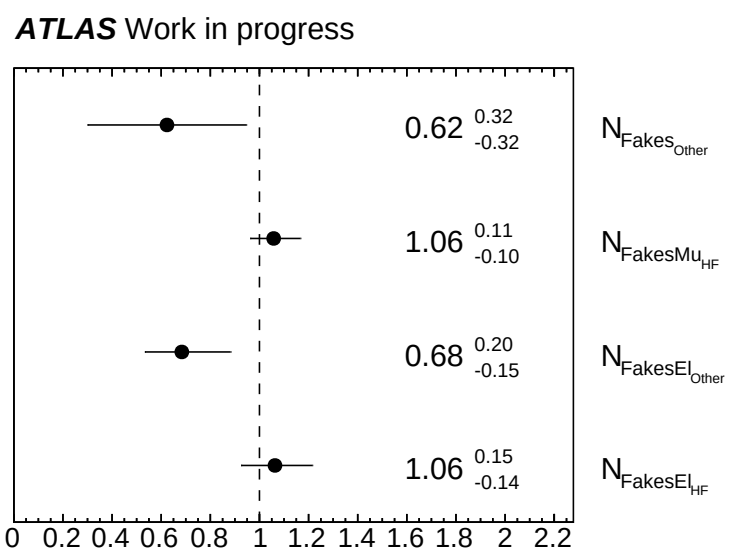


Figure 5.9: The normalisation factors for the four different samples, with their total uncertainty.

Chapter 6

Multivariate analysis

This chapter is dedicated to the presentation of the MVA analysis, performed with the goal of improving the separation between the signal and the background sources. I will begin the chapter with a brief introduction on the theoretical background for MVA analysis, which will then be followed by a description of my analysis. I will present the results split between the three different event selections of Table 4.5, respectively in Sections 6.2 to 6.4 for **Default**, **Loose** and **Medium**. Out of the huge amount of NN trainings performed, I will present only the most significant ones, which are the ones for which a fit was then performed. The results will be presented chronologically as they were obtained during the analysis.

6.1 Theoretical background

ML is a branch of Artificial Intelligence devoted at building algorithms that learn, that is, methods which leverage data to improve performance on some set of tasks. For this thesis I have been performing Supervised ML (SML), which works as follows: the user provides the machine a dataset, in which the entries are labelled as belonging to some specified classes. The dataset is then split into *training* and *validation* datasets. The machine then uses the *training* dataset to train itself with a Neural Network (NN) at classifying the events, learning how to discriminate the different classes and building a discriminant variable. The *validation* dataset is then used to check how right the machine has been able to learn. The training stops when the loss function arrives at a minima, and in a well-performed training the validation and the training loss functions must converge. As an output, the machine provides a variable which maximises the separation between the classes.

An MVA analysis is the best way to create a variable which best separates the signal from the backgrounds, variable which will then be used for the fit. The variable, or variables in case of a Multi Class, is generated by training a classifier Neural Network on the Monte Carlo samples. A scheme of a Deep Neural Network, similar to the ones used in this analysis, is presented in Figure 6.1.

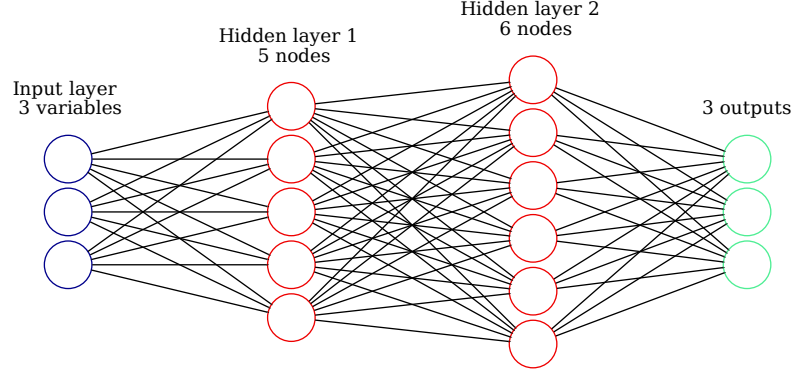


Figure 6.1: Example of a multiclass Deep NN with two hidden layers.

In order to perform the training, the following things must be selected:

Event selection

The input data must be big enough to allow the NN to train itself, especially considering that only 75% of the input data is used for the training, with the remaining being used for the validation. Therefore, using a looser event selection with higher event yields is expected to improve the training. Nevertheless, this does not guarantee that the fit will necessarily be better, because the fit will then have to deal with more backgrounds. Additionally, splitting the event selection into regions narrowing down the phase space can also improve the training, in spite of a lower input size.

Input variables

The NN takes some input variables in order to perform the training. The more the input variables are able to separate the signal from the backgrounds, the better the NN output will separate the different sources. Using too many variables may lead to *overtraining*, which is when the NN learns from statistical fluctuation instead of training itself.

Classifier type

The type of classifier denotes the number of outputs:

- i) Binary classifier: Two different targets are given to the NN: Signal (1) and Background (0). Therefore, all the backgrounds are treated the same, and the NN learns how to discriminate the signal from all the background sources. There is a single output variable, whose value for background is 0 and for signal is 1.

- ii) Multi-Class classifier: There are N targets given to the NN, with $N > 2$. Signal is always target 0, whereas each additional target N_i refers to a different background source. The number of output variables O_i generated is N , with $\sum_{i=1}^N O_i = 1$ for each event. For instance, in a multiclass with 3 classes (MC-3), the targets can be Signal (0), $t\bar{t}Z$ (1) and all the other backgrounds (2). The outputs will then be O_{tZq} , $O_{t\bar{t}Z}$ and O_{Others} , and for each event $O_{tZq} + O_{t\bar{t}Z} + O_{Others} = 1$. In this thesis, both a multiclass with 3 classes and with 4 classes (MC-4) were used.

Hyperparameters

The hyperparameters represent the set of parameters that define the Neural Network. Such parameters include:

- i) Loss function: the loss function is the function that measures how good the model is performing the classification task. For Binary NNs, the loss function used is `binary_crossentropy`, defined as $J(\vec{\omega}) = -\frac{1}{n} \sum_{i=1}^n y_i \log(\hat{y}_\omega(x_i)) + (1 - y_i) \log(1 - \hat{y}_\omega(x_i))$, where y_i is the target, $\hat{y}$ is the model output, n is the number of neurons of the NN and $\vec{\omega}$ is the parameters vector. On the other hand, for a Multiclass NN, the loss function is the `categorical_crossentropy` $J(\vec{\omega}) = -\sum_{i=1}^n y_i \log(\hat{y}_\omega(x_i))$. These two functions have never been changed throughout the analysis, as they are known to be the optimal choices for the two classifier.
- ii) Learning rate: the learning rate η is the factor that specifies how fast the NN parameters are updated at each iteration, since $\omega_i = \omega_i - \eta \vec{\nabla} J$. The learning rate cannot be too small, because otherwise the parameters are updated too slowly and the training stops before reaching convergence, but it cannot also be too big, because that can lead to divergence. This parameter has been changed multiple times throughout the analysis in order to find the better one for each training.
- iii) Number of hidden layers: In a Deep Neural Network, at least one hidden layer of neurons is implemented. This number can change, and in this analysis numbers between 2 and 5 have been tested.
- iv) Number of nodes per layer: This number, alongside the number of hidden layers, tells how complicated the NN is. Increasing the number of neurons at first improves the training, but after a certain point the NN reaches *overtraining* if it gets too complicated. This number has been changed for all the different NNs tested.
- v) Dropout: The dropout is an option that allows the NN to turn off some neurons with a certain rate, consequently making the training the more general as possible. Dropout rates used in this analysis are between 0.2 and 0.4.
- vi) Batch size: It refers to the number of samples which are used for the training at each step before updating the parameters. For this thesis, both small (32 or 64) and large (5000) sizes have been used.

- vii) Activation functions: Activation functions are the functions used to generate the connections between neurons in different layers. Those functions are non-linear, and the ones tested in this analysis are *ReLU*, *Elu*, *tanh* and *sigmoid*.
- viii) Cross-validation algorithm: The algorithm used for the cross-validation is k -fold. This technique consists in splitting the training dataset in k folds, of which $k - 1$ are used for training and the remaining one for validation. The process is iterated k times, each time changing the set used for validation. In this thesis both 3 and 4 folds were used.

These hyperparameters are chosen through *hyperparameter optimisation*, which refers to the **Grid Search** test of those parameters in order to find the setup which returns a better training.

Evaluation

In order to decide which is the best NN among multiple trainings, there are few things to be looked at.

First of all, in order for a training to be correctly completed, the loss function and the accuracy for validation and training must converge asymptotically. A training in which this does not happen is a training which was not completed correctly, and therefore is not able to correctly discriminate between the target classes. Additionally, among converging trainings the best one is the one with the lower loss function.

Secondly, we want the trainings to be able to best separate the signal from the backgrounds. Therefore, for each training the separation value S between the signal distribution N_S and the background distribution N_B , defined in Equation (6.1.1), was evaluated, where N_{S_i} refers to the number of signal events in the i -th bin. The training with best separation was chosen, among the converging ones with a low loss function.

$$S = \frac{1}{2} \sum_{i=1}^{N_{bins}} \frac{(N_{S_i} - N_{B_i})^2}{N_{S_i} + N_{B_i}} \quad (6.1.1)$$

Additionally, the ROC (*Receiver Operating Characteristic*) curve, which plots the true positive rate versus the false positive rate, and its integral the AUC (Area Under ROC) are looked at. A perfect training would have a horizontal ROC at the value 1, and its integral would be 1 as well. The best trainings are the ones for which the AUC is closer to 1. An example of a ROC curve is shown in Figure 6.2(a).

Finally, the last parameter considered when comparing different trainings is the *Confusion Matrix*. It is a matrix where the primary diagonal elements show the false positive rate and the false negative rate, whereas the secondary diagonal elements are the true positive and negative rates, as shown in the example in Figure 6.2(b).

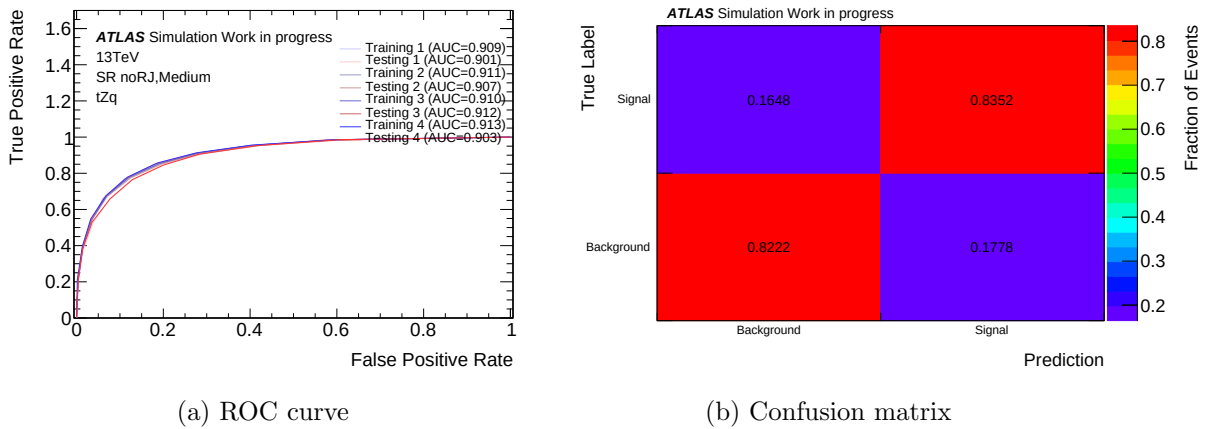


Figure 6.2: Examples of ROC curve (left) and confusion matrix (right).

6.2 Default selection

In this section, I will present the NN trainings using the `Default` selection (Table 4.5), whose yields are reported in Table 4.6. The signal contribution is almost 20% of the total yields, with the remaining events coming mainly from $t\bar{t}Z$ (39%), VV (21%) and Fakes (11%). Therefore, it seemed convenient to perform, in addition to the Binary training, multiclass trainings with tZq , $t\bar{t}Z$, VV and Fakes as target, either for 3 or 4 classes. Binary trainings will be presented in Section 6.2.1, whereas MC-4 will be reported in Section 6.2.2.

6.2.1 Binary

The first tests we made were with the Binary classifier. As aforementioned, we define two classes, signal and backgrounds, and the NN train itself at separating between the two.

Binary with all regions together

For the first training, the simplest setup was implemented. Only one region was defined, as per Table 4.5, using all the events for the training. This may not seem like the optimal setup, because both signal and backgrounds have different shapes based on jet multiplicity. Therefore, a training in which only some similar jet multiplicity regions are used could give better results than this, as I will present later on. On the other hand, using all the regions together helps the training in that more statistics is given, because all the available events are used.

The variables used for this training are reported in Table 6.1. The variables were selected so that they were not too correlated, as seen in Figure 6.3, and such that the shapes of different samples are different enough to help the NN on separating them. The hyperparameters were optimised using the `Grid search` algorithm, and the best setup was obtained with the following set of parameters:

Variable	Definition
$m(b, j_f)$	Invariant mass of the b -jet+forward-jet system
m_{top}	Reconstructed mass of the top quark
$ \eta(j_f) $	Absolute value of pseudorapity for the forward jet
H_T	Squared sum of transverse momentum of all leptons and jets
$m_T(W)$	Transverse mass of the reconstructed W boson
$Q(\ell_W) \cdot p_T(\ell_W)$	Product between charge and p_T of lepton coming from W boson
$m_{\ell\ell}$	Invariant mass of the dilepton system coning from Z
$p_T(W)$	Transverse momentum of reconstructed W boson
$ \eta(\ell_W) $	Absolute value of pseudorapity of ℓ_W
$ \eta(Z) $	Absolute value of pseudorapity of reconstructed Z boson
$\Delta R(j_f, Z)$	Radius difference between forward jet and reconstructed Z boson
$p_T(j_f)$	Transverse momentum of forward jet
E_T^{miss}	Missing transverse energy, defined in Equation (4.4.4)

Table 6.1: List of variables used for the Binary training

- Input layer: 13 nodes (input variables)
- 3 layers
- Nodes in each layer: 20, 14, 9
- Activation functions: *ReLu*, *ReLu*, *ReLu*
- Batch size = 1000
- Learning rate = 0.00008
- No dropout rate or batch normalisation layer
- 3 folds for cross-validation

Since 3 folds were used, 3 loss functions were generated. However, here I will show the loss function for only one fold, since all the three functions converged to the same values, around 0.5. The plot is displayed in Figure 6.4, alongside the ROC curve, whose AUC values are all above 0.83.

Figure 6.5(a) shows the separation plot, in which the fraction of events for signal and backgrounds are shown as a function of the NN output. The separation for this training is 34%, which we will take as baseline for comparison with the other trainings. In Figure 6.5(b) the stack plot for the tZq classifier is presented. It can be seen how the classifier worked correctly especially for $t\bar{t}Z$ and Diboson, as they all peak in the first bins before decreasing rapidly in the high-value bins. Contrarily, the signal peaks in the final bins. The other background sources are not treated as good because their contribution is smaller.

The results of the fit using this selection will be presented in Section 7.2.1.

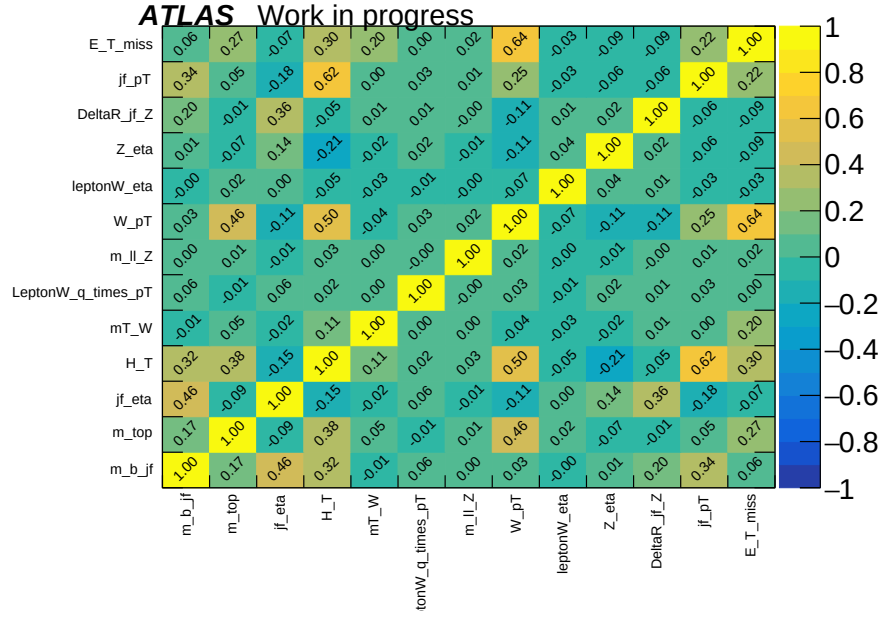


Figure 6.3: Matrix which shows the correlation between the input variables.

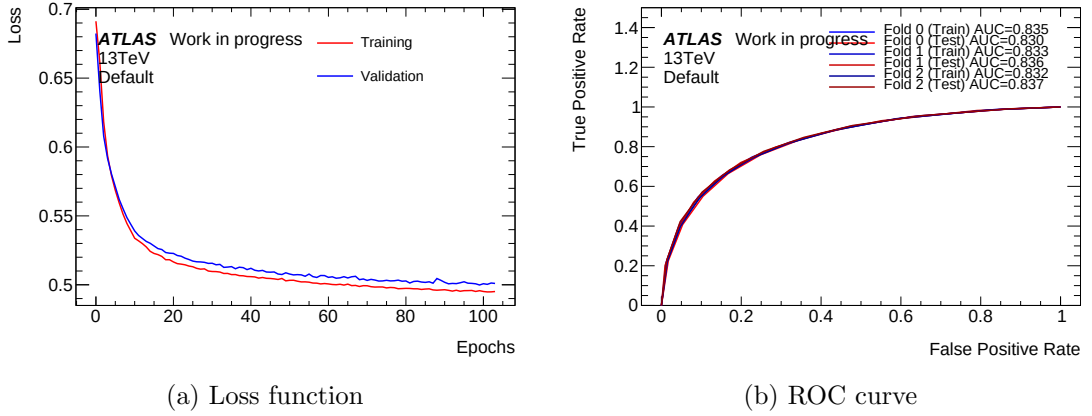


Figure 6.4: Loss function (left) and ROC curve (right) for the Binary training.

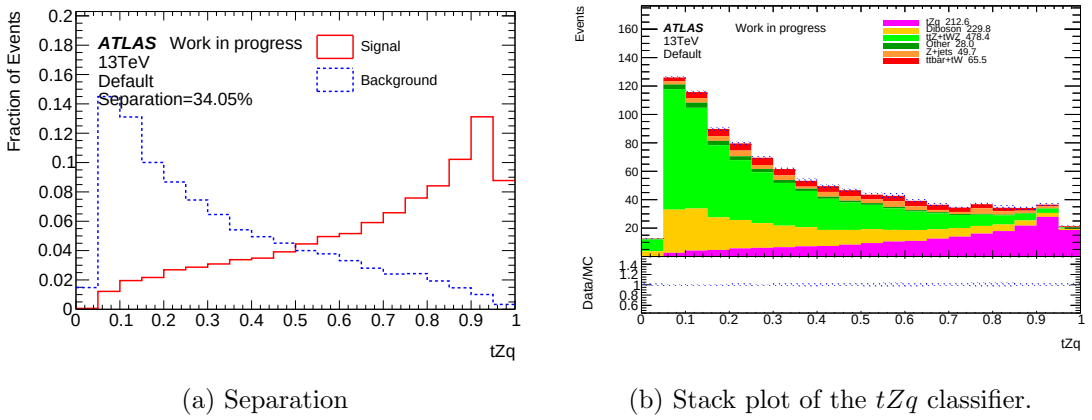


Figure 6.5: Separation (left) and stack plot (right) for the Binary training.

Binary splitting regions

As stated earlier, the advantage of training all the events together is that the different shapes of the samples are not exploited. Therefore, at the cost of reducing the input size, an alternative setup was tested. This time, two different NNs were trained, in two orthogonal regions defined by the presence of a radiation jet. The regions with a radiation jet, defined as **RJ**, includes *3j1b* and *4j1b*¹¹ events, whereas the region without a radiation jet, labelled as **no-RJ**, is made of *2j1b* and *3j2b* events. The *4j2b* region is excluded from the training. An additional advantage of this setup is that it allows us to use some variables that are defined only in some specific regions as input, such as radiation jet variables.

This training, with respect to the previous one, has a lower statistics, which could deteriorate the NN performance. However, splitting the regions could also bring an improvement to the overall training, for the reasons stated earlier. Additionally, this could bring improvements in the fit, because the same split could be implemented there as well.

The variables used for this training in the **no-RJ** region are the same as the ones reported in Table 6.1, whereas in the **RJ** region the variables $|\eta(j_r)|$, $p_T(j_r)$ and $p_T(Z)$ were used instead of H_T , $m_{\ell\ell}$ and E_T^{miss} .

The signal yields for the two regions are reported in Table 6.2.

Sample	no-RJ	RJ
tZq	118.1 ± 17.3	72.8 ± 13.0
$VV + b$	72.6 ± 2.7	43.7 ± 1.6
$VV + c$	44.8 ± 1.7	23.9 ± 0.9
$VV + l$	8.0 ± 0.4	4.3 ± 0.2
$t\bar{t}Z$	128.9 ± 13.3	174.5 ± 14.0
$t\bar{t}W$	7.8 ± 0.3	4.5 ± 0.2
tWZ	24.3 ± 9.6	26.7 ± 11.3
$t\bar{t}H$	4.4 ± 0.2	4.8 ± 0.2
Fakes	68.2 ± 4.6	26.5 ± 1.5
Total	477.0 ± 28.6	381.6 ± 25.0

Table 6.2: Event yields for the two different regions used in the training. Uncertainties are statistical-only

The best hyperparameters were selected once again with the **Grid search** algorithm, and the best configuration turned out to be the same for both trainings:

- Input layers: 13 nodes (input variables)
- 2 layers
- Nodes in each layer: 20, 11
- Activation functions: *ReLu*, *ReLu*

¹¹The *njmb* notation refers to *n* jets, of which *m* *b*-jets.

- Batch size = 1000
- Learning rate = 0.0001
- No dropout rate or batch normalisation layer
- 3 folds for cross-validation

Once again, I will present only one loss function for each training. The functions are displayed in Figure 6.6, where it can be seen that for both trainings there is an asymptotic convergence. The number of epochs differs because the *early stopping* technique was used, which stops the training if the training curves do not change too much after a certain number of iterations, in order to avoid overtraining.

Figure 6.7 presents the ROC curves for both trainings. The ROC curves for all training and testing values are above 0.85, except for one in the RJ training, but this does not negatively affect the overall training, as its loss function (Figure 6.6(b)) is converging.

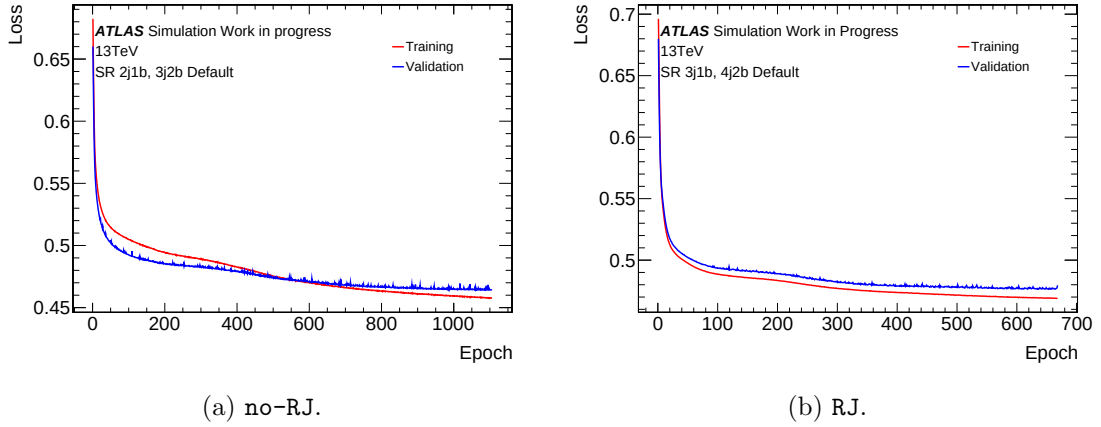


Figure 6.6: Example loss functions for the no-RJ (left) and RJ (right) NN Binary trainings.

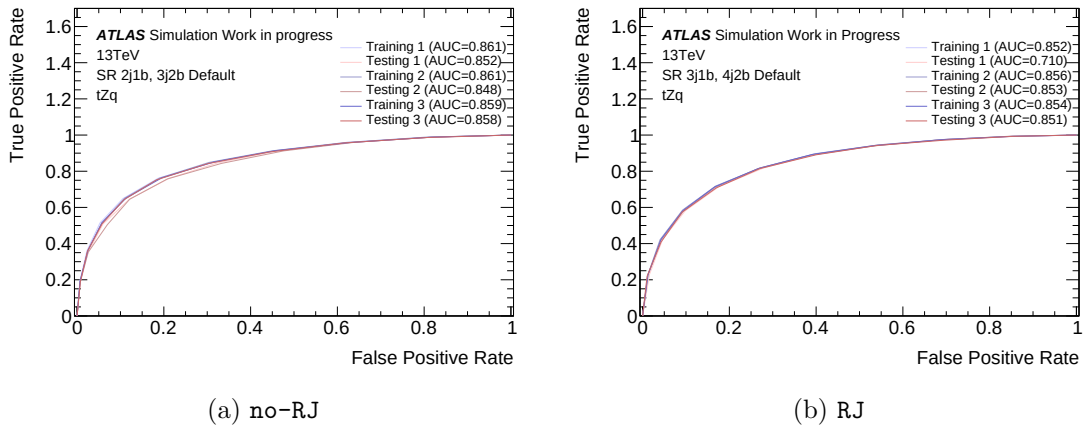


Figure 6.7: ROC curve for no-RJ (left) and RJ (right)

Furthermore, for this training I will also present the ranking of the input variables in Figure 6.8. The variables are ranked based on the impact they had on the training, focusing on how much the AUC would be different if that variable was excluded from the training. From this ranking we can see how the radiation jet variables impacted the training, and we note that it was mostly $p_T(j_r)$ who contributed to the good outcome of the training, having an impact close to 5%. On the other hand, the pseudorapidity of the radiation jet had a negligible impact on the training. What stands out the most about this ranking is that $m(b, j_f)$ and $\Delta R(j_f, Z)$ are the two variables with the greatest impact in both regions.

Finally, the confusion matrices all have diagonal elements above 0.75, hence confirming that the training performed well.

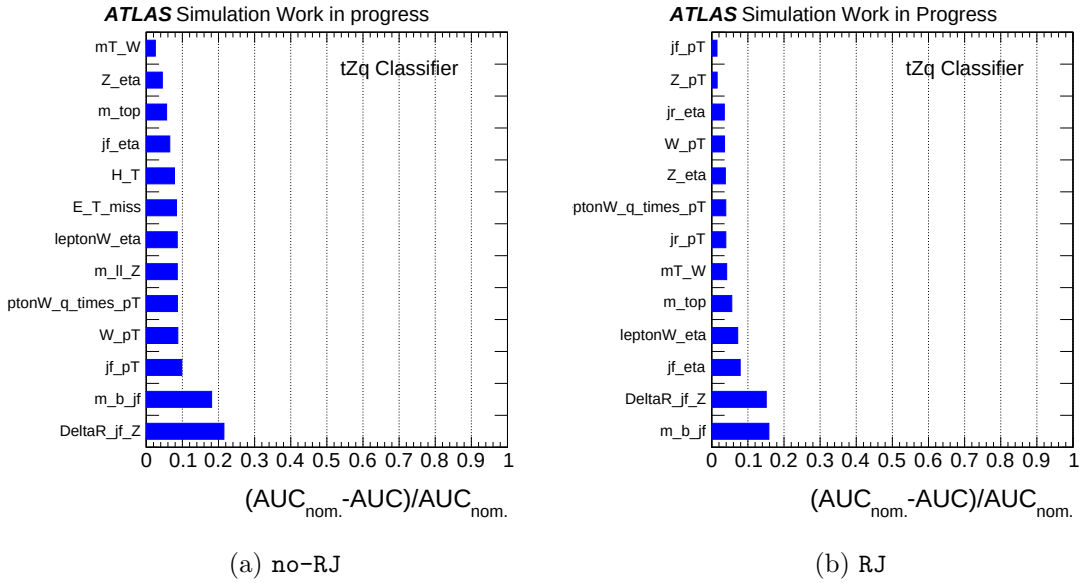


Figure 6.8: Input variables ranking for the two separate trainings.

The separation plots are shown in Figure 6.9. The separation values are higher than what was obtained with the single training with all the events together, and the stack plot of the NN output (Figures 6.10(a) and 6.10(b)) shows how both NNs were able to correctly treat all the backgrounds, because their distributions all peak in the first bins, before decreasing as the output nears 1. In particular, more than 25% of both Diboson and $t\bar{t}Z$ are found in the first two bins for both classifiers, whereas the signal contributes for more than 85% in the last bin. Consequently, we expect a fit to work better than the one with the previous training. The results for the fit which uses this training will be presented in Section 7.2.1.

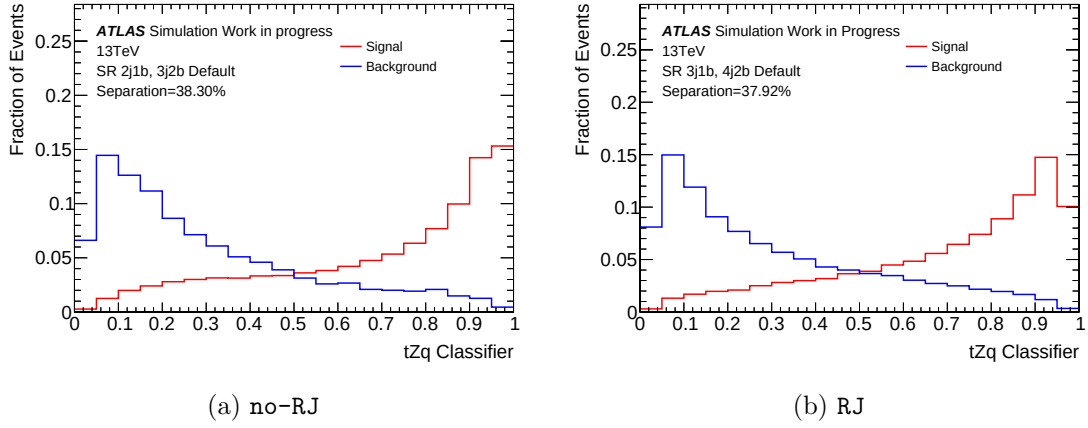


Figure 6.9: Separation plots for no-RJ (left) and RJ (right)

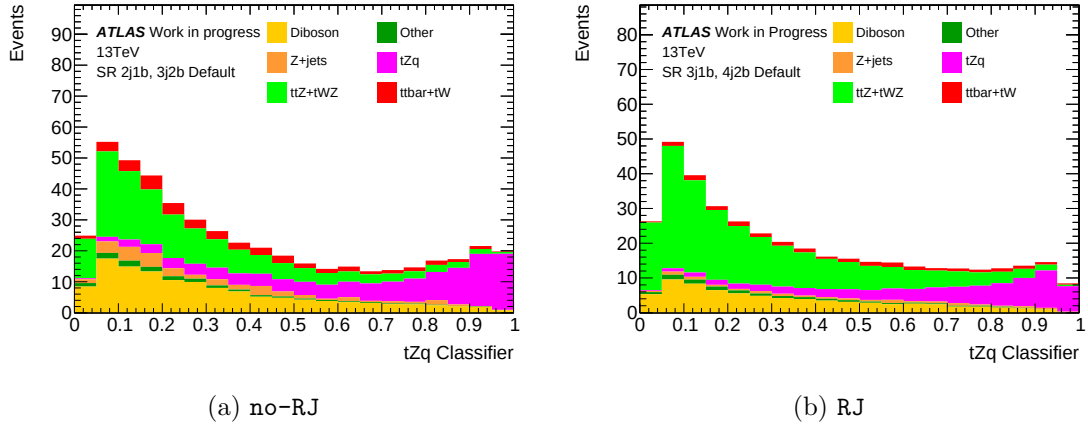


Figure 6.10: NN output stack plots for no-RJ (left) and RJ (right)

6.2.2 Multi Class: 4 classes

For the two binary trainings shown above the fit is made using only signal regions, because different background sources-enriched regions cannot be defined using the NN output. The idea behind using background-enriched regions (also labelled as control regions, CRs) is that if in those regions there is mostly one type of background, the systematics regarding the background are better treated, as well as the uncertainties on their normalization, henceforth resulting in a lower total uncertainty. By contrast, using a multiclass deteriorates the training performance, because multiple outputs are generated, with their sum equalling 1 for each event. Therefore, separation values are lower, as well as diagonal elements in the confusion matrix and the loss function convergence value.

Consequently, aiming for this lower cross-section uncertainty, which will be extracted by the fit, we tried to perform a Multiclass NN training. Multiple attempts have been made with a multiclass with 3 classes, which will be summarised in Table 6.10, whereas in the following I will present the training with 4 classes.

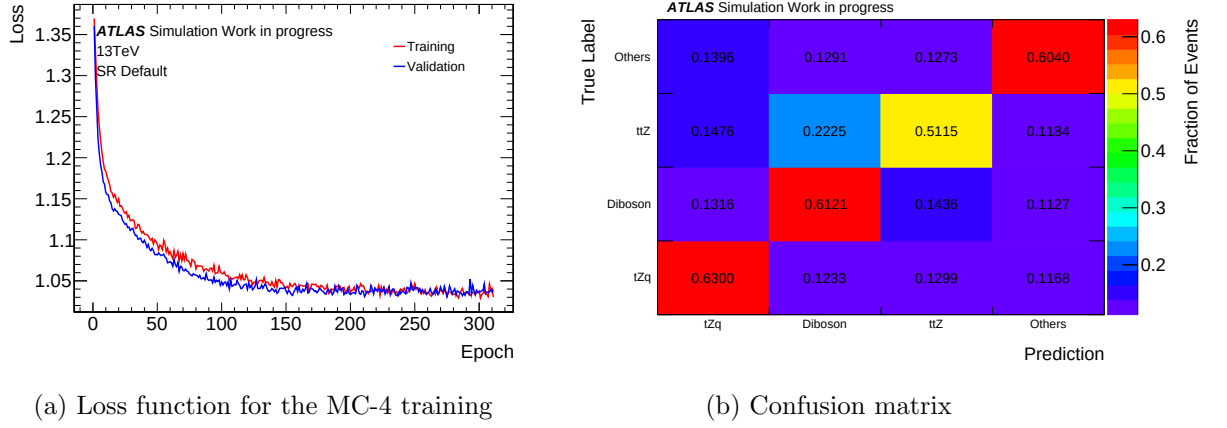


Figure 6.11: Loss function (left) and confusion matrix (right) for the MC-4 NN training.

The 4 NN classes (targets) are signal (0), $t\bar{t}Z + tWZ$ (1, labelled as $t\bar{t}Z$), VV (2) and Others (3), which includes mostly Fakes. These targets were chosen as they are the ones with greater yields. 24 input variables were used for this training, represented in Table 6.3. In particular, the N_{jets} variable, which refers to the number of jets for each event, was added because the different backgrounds usually favour a different jet multiplicity.

The hyperparameters from the **Gris search** algorithm were:

- Input layers: 24 nodes (input variables)
- 4 layers
- Nodes in each layer: 20, 30, 30, 20
- Activation functions: $ReLU$, $ReLU$, $ReLU$, $ReLU$
- Batch size = 5000
- Learning rate = 0.0005
- Dropout rate = 0.3, on layers 0,1,2
- No batch normalisation layers
- 3 folds for cross-validation

The loss curve for one of the folds is presented in Figure 6.11(a), alongside the confusion matrix. As predicted, the loss curve converges to a lower value, and the confusion matrix diagonal elements have lower values than the ones obtained in the previous two binary trainings, because if 4 targets are given, it is less likely that the prediction will be correct. Nevertheless, the training worked correctly, as the AUCs in Figure 6.12 are all above 0.70, with the majority of them being over 0.80.

Variable	Definition
$m(b, j_f)$	Invariant mass of the b -jet+forward-jet system
m_{top}	Reconstructed mass of the top quark
$p_T(top)$	Transverse momentum of the top quark
$Q(\ell_W)$	Charge of the lepton coming from W boson decay
$p_T(W)$	Transverse momentum of W boson
$m_T(W)$	Transverse mass of the reconstructed W boson
$ \eta(\ell_W) $	Absolute value of pseudorapidity of ℓ_W
$p_T(\ell_W)$	Transverse momentum of lepton coming from W boson decay
$m_{\ell\ell}$	Invariant mass of the dilepton system coming from Z
$j_b(\text{b-tagging})$	b -tagging score of b -jet
$p_T(j_b)$	Transverse momentum of b -jet
$ \eta(j_b) $	Absolute value of pseudorapidity for the b -jet
$j_f(\text{b-tagging})$	b -tagging score of forward jet
$p_T(j_f)$	Transverse momentum of forward jet
$ \eta(j_f) $	Absolute value of pseudorapidity for the forward jet
$ \eta(Z) $	Absolute value of pseudorapidity of reconstructed Z boson
$p_T(Z)$	Transverse momentum of reconstructed Z boson
$\Delta(m_Z, m_{\ell\ell})$	Difference between invariant mass of reconstructed Z boson and $m_{\ell\ell}$
$\Delta\phi(W, j_{\text{closest}})$	Azimuthal difference between W boson and forward jet
$\Delta\phi(top, Z)$	Azimuthal difference between top quark and reconstructed Z boson
$\Delta R(j_f, Z)$	Radius difference between forward jet and reconstructed Z boson
$\Delta R(top, Z)$	Radius difference between top quark and reconstructed Z boson
$\Delta R(j_f, \ell_W)$	Radius difference between forward jet and lepton coming from W boson
N_{jets}	Number of jets

Table 6.3: List of variables used for the Multi class training

For this training as well, I am presenting also the input variable ranking for all four classifiers (Figure 6.13). We can note how the $\Delta R(\ell_W, j_f)$ is among the leading variables in almost all classifiers. Moreover, we observe that the Number of Jets variable, though not having a great impact on the tZq classifier, is really important for the $t\bar{t}Z$ and VV classifiers, which justifies why this variable was added. Finally, we observe that $p_T(W)$ does not impact significantly any of the trainings.

The separation values are lower than before, as expected, with separations and stack plots being presented in Figure 6.14. The highest separation is obtained for the *Others* classifier, followed by tZq , VV and $t\bar{t}Z$. In spite of this being the best training, it can be seen that especially the $t\bar{t}Z$ classifier has not been able to perform correctly on its target, since the $t\bar{t}Z$ distribution is almost flat. On the other hand, the target distributions for the tZq , VV and *Others* classifiers all increase up until a value of around 0.7, before decreasing and having almost no contribution in the last bins.

The additional interesting plots that can be generated for a multiclass are the 2D response plots, which are plots showing how the events belonging to a particular sample are located with respect to two classifiers. These plots can be used to generate control

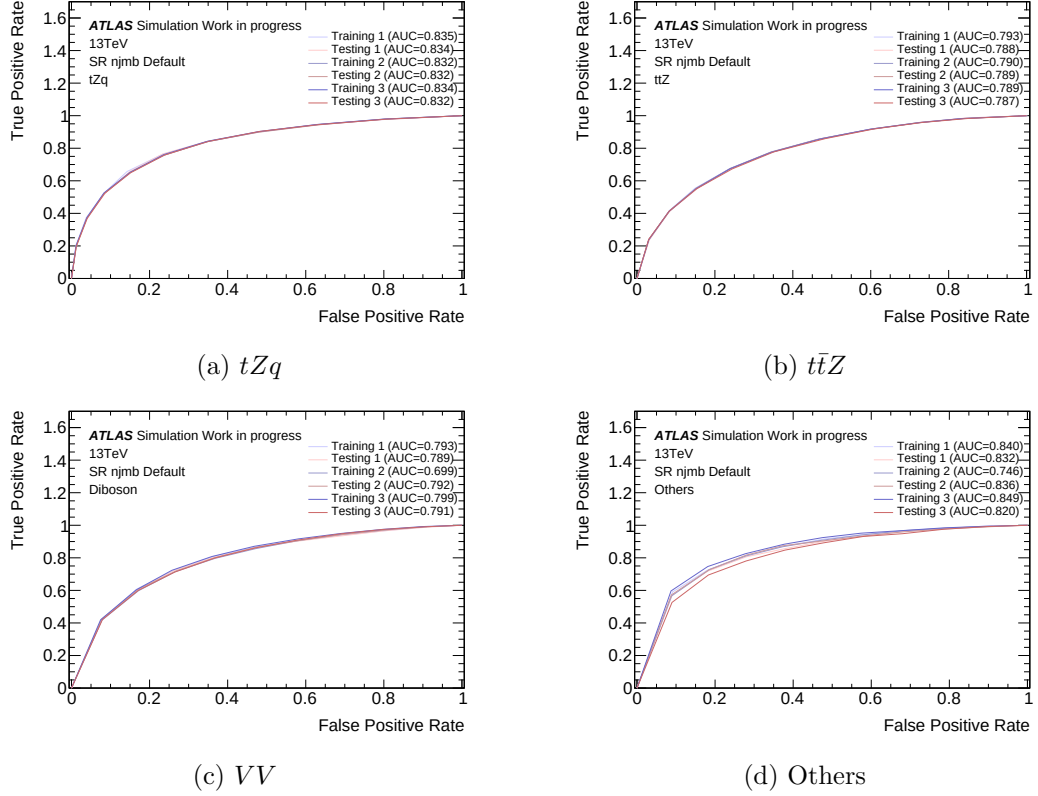


Figure 6.12: ROC curves and AUC for all the four classifiers, all showing values above 70%.

regions, by making cuts on the classifier scores, because they tell how to make the cuts in order to obtain the regions with the highest contribution of each sample. Particularly interesting is the signal significance 2D response plot, which tells for which values of two classifiers the highest signal significance is obtained. An example of this can be seen in Figure 6.15(d), where the highest signal significance is obtained when ttZ score is 0.31 and VV score is 0.42. This means that the region with $ttZ < 0.42$ & $VV < 0.42$ is a signal-enriched region. This is confirmed also by the tZq 2D response plot (Figure 6.15(a)), where it can be noted how the signal contribution outside the region is negligible. The other two 2D plots (Figures 6.15(b) and 6.15(c)) reflect the considerations made earlier. The ttZ response is almost flat with respect to the ttZ classifier, as noted also in Figure 6.14(a), whereas it responds well against Diboson, because it is mostly located in the region with $VV < 0.3$. On the contrary, the Diboson score is well localised for both VV and ttZ classifiers. These three plots were used later on to define the regions for the fit.

I will not be presenting here the other 2D response plots since those regions were not used for the fit.

The fit's results using this classifier are presented in Section 7.2.1.

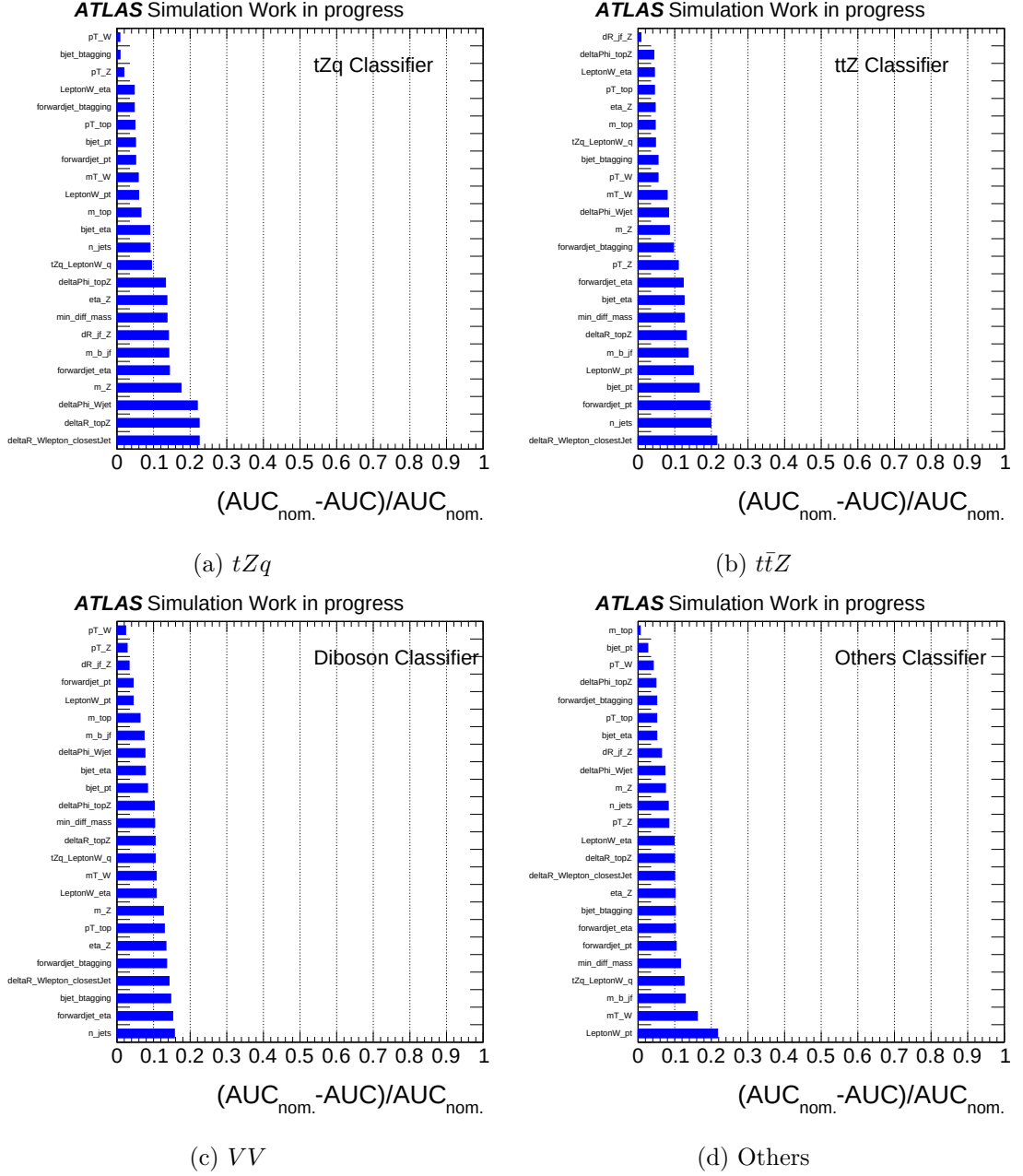


Figure 6.13: Input variables ranking for the four classifiers.

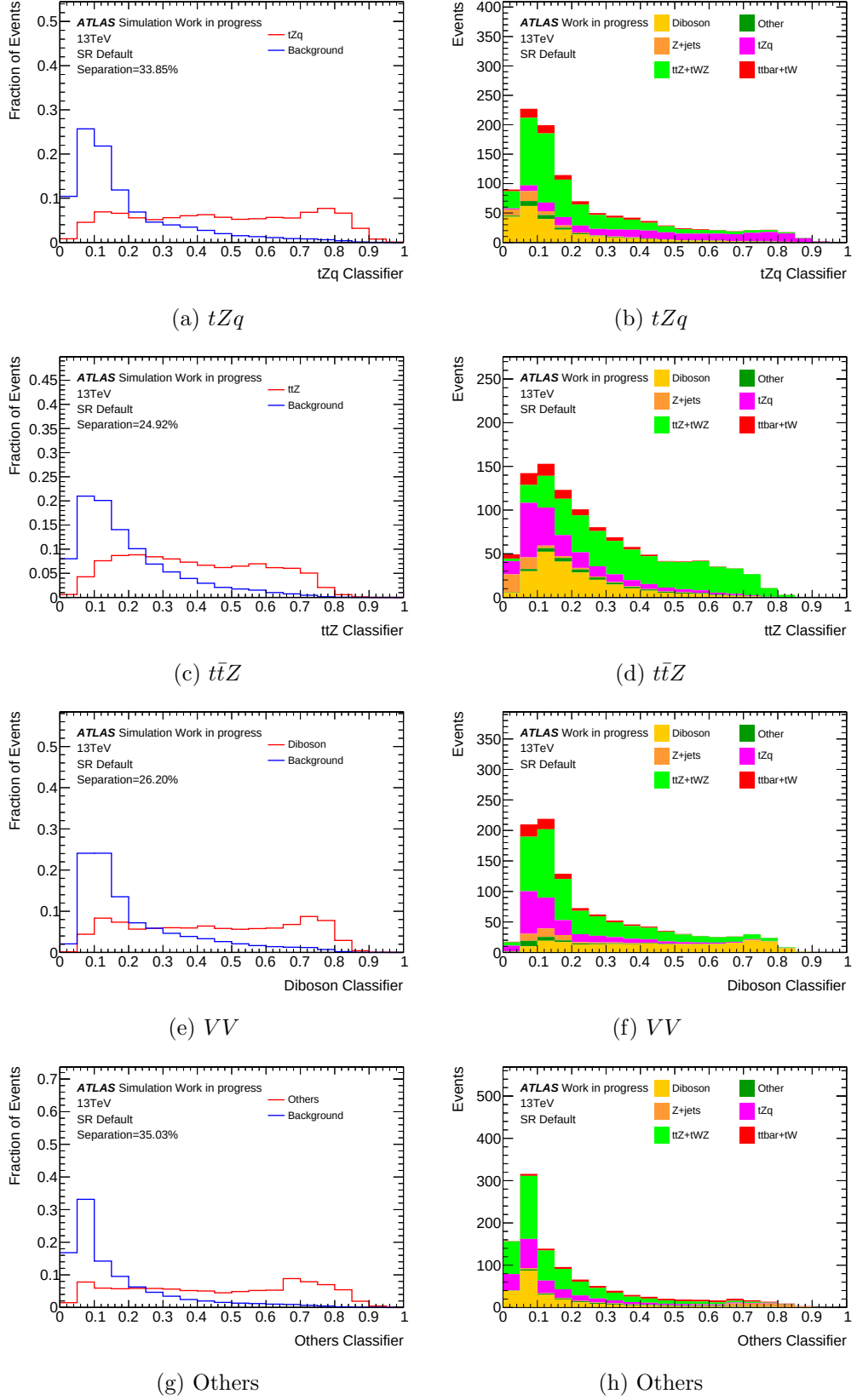


Figure 6.14: Separation curves (left) and stack plots (right) for all the four classifiers.

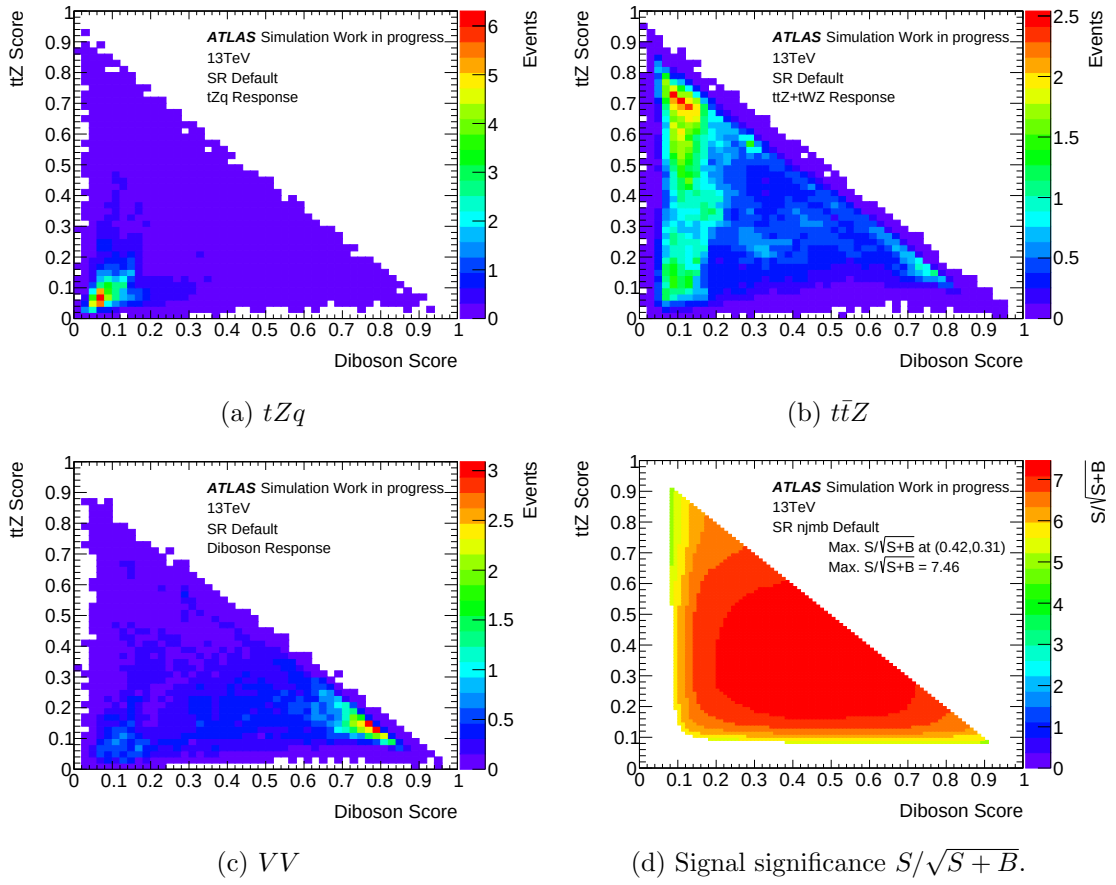


Figure 6.15: Response plots in the 2D $t\bar{t}Z$ vs Diboson plane, for tZq , $t\bar{t}Z$ and Diboson in the first three pictures, respectively. The bottom right plot displays the signal significance.

6.3 Loose selection

This section is dedicated to the NN trainings performed using the **Loose** selection. We decided to change the event selection and use a looser one in order to try and gain as much signal as possible. This not only helps the training, but it can also have a positive impact on the final uncertainty on the cross section.

The event selections and the yields are reported in Tables 4.5 and 4.6, respectively. The signal contribution is less than the **Default** selection, at 10.7%, although the total signal yields increased by 37%. The fakes are the background which increased the most, because isolation WPs have a lower background rejection at low p_T , and this selection has lower thresholds for $p_T(\ell)$. Additionally, the Diboson without b -jets (so $VV + c$, $VV + l$) background increased significantly, because the b -jet efficiency was increased to 85%, thus resulting in a lower c - and l -jet rejection, as per Table 4.3. Likewise, also $VV + b$ rose, although this increase was of only 107% as opposed to more than 1000% for the lighter flavours.

For this selection, different NNs were tested. In the following I will present a binary training and a multiclass with 3 classes. Other configurations will not be shown because they were not used for the fits, since we quickly realised that the **Medium** selection could bring better results. Nevertheless, these two trainings and their fit results will be presented for completeness. In these trainings, all the fakes background sources ($t\bar{t}$, tW and Z +jets) were merged together into the *Fakes* sample.

6.3.1 Binary

Similarly to the **Default** selection, the first training was performed with a Binary NN. The aim of this test was to compare both the training and the fit results with the same setup. Therefore, this training is made keeping all the regions together, using the same variables as in Table 6.1, with the addition of $p_T(Z)$ and **bjet_btagbin**, a variable which returns a binned distribution of the b -tagging WP score for the jet tagged as b -jet. The value that this variable can hold are presented in Equation (6.3.1).

$$\text{bjet_btagbin} = \begin{cases} 1 & \text{if } b\text{-tagging score} > 85 \\ 2 & \text{if } b\text{-tagging score} \in [77, 85] \\ 3 & \text{if } b\text{-tagging score} \in [70, 77] \\ 4 & \text{if } b\text{-tagging score} \in [60, 70] \\ 5 & \text{if } b\text{-tagging score} < 60 \end{cases} \quad (6.3.1)$$

Despite the input variables being almost the same, the optimised set of hyperparameters looked quite different from **Default**'s:

- Input layers: 15 nodes (input variables)
- 3 layers

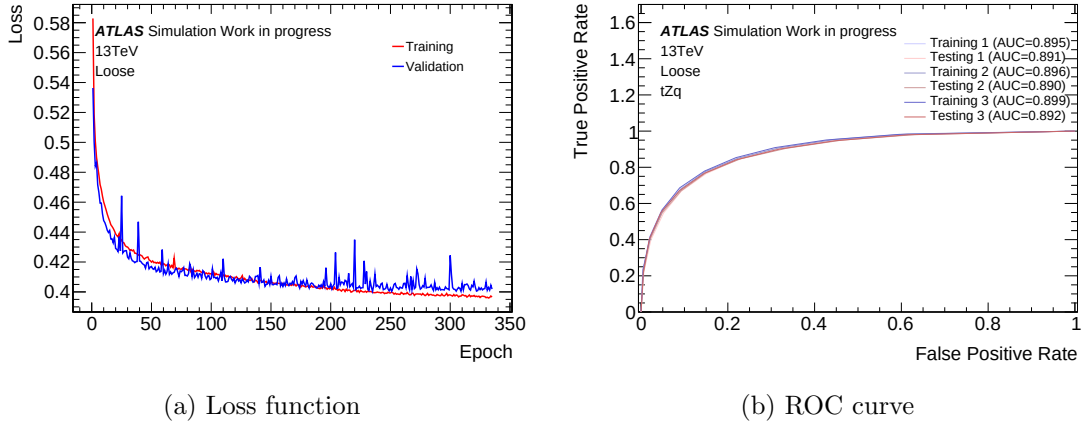


Figure 6.16: Loss function (left) and ROC curve (right) for the Binary training.

- Nodes in each layer: 22, 17, 11
- Activation functions: *ReLU*, *ReLU*, *ReLU*
- Batch size = 1000
- Learning rate = 0.0005
- No dropout or batch normalisation layers
- 3 folds for cross-validation

The loss function is shown in Figure 6.16(a), and it can be seen how, in spite of some fluctuations in the validation, there is a convergence between the two curves. Moreover, we can see how the convergence is reached at a lower value than it was for **Default**. We expected this to happen because the whole dataset is almost three times the size of **Default**'s, henceforth it is easier for the NN to train itself on classifying signal and backgrounds. ROC curve (Figure 6.16(b)) and confusion matrix also tell that this training's performance was better than the **Default** selection's training.

However, the best confirmation that this training was better than the **Default**'s comes from the separation curve and the stack plot, displayed in Figure 6.17. The separation grew by a staggering 13%, reaching a value of 47%. This is the best training so far, as we can see that the fraction of background with a NN output higher than 0.5 is never higher than 5% in each bin, and especially in the final bins the contribution is less than 2%. On the contrary, the signal follows an opposite pattern. In the first bins the contribution is less than 2%, rising to 5% in the middle (tZq score = 0.5) before increasing rapidly to 25% in the final bin. Moreover, the stack plot tells us that all the background sources are treated correctly, with Fakes and Diboson peaking in the first two bins respectively, with more than 45% of their total located there, whereas for $t\bar{t}Z$ the peak is a little bit to the right, at around 0.25. Additionally, the signal contribution in the last bin is almost 4 times greater than the backgrounds'.

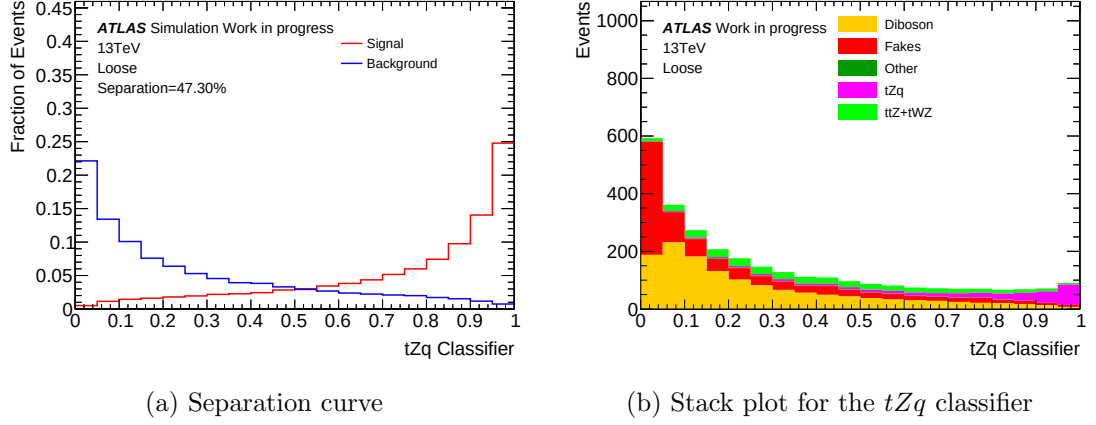


Figure 6.17: Separation curve (left) and stack plot (right) for the Binary training.

In conclusion, we can state that the **Loose** selection training was better than **Default**'s. Therefore, we expect also the fit, whose results are reported in Section 7.2.2, to perform better with this looser selection.

6.3.2 Multi Class: 3 classes

Similarly to what was done with the **Default** selection, we decided to try and test a MC-classifier in order to generate background-enriched regions to be used for the fit. This time however, I will present a multiclass with 3 classes (MC-3).

Because the binary classifier did not work as good on $t\bar{t}Z$ as it did on Fakes and Diboson, we decided to test a multiclass using $t\bar{t}Z$ as the target, thus having the following outputs: tZq (0), $t\bar{t}Z$ (1) and Others (2), with the latter including Fakes, Diboson and the small contributions from $t\bar{t}H$ and $t\bar{t}W$.

Both the variables used in the **Loose** Binary and in the **Default** MC-4 were tested, with the former giving the best result. The hyperparameter optimisation returned this set:

- Input layers: 15 nodes (input variables)
- 2 layers
- Nodes in each layer: 20, 11
- Activation functions: *ReLU*, *ReLU*
- Batch size = 1000
- Learning rate = 0.0005
- No dropout or batch normalisation layers
- 3 folds for cross-validation

The increased statistics for this training improved significantly the performance of this NN as well. This result however is not due to the increase in statistics only, but it is also due to the fact that 3 classes are used instead of 4. Nevertheless, the same improvement in the training was reached with the MC-4 classifier for the Loose selection, as Table 6.10 in the Summary displays.

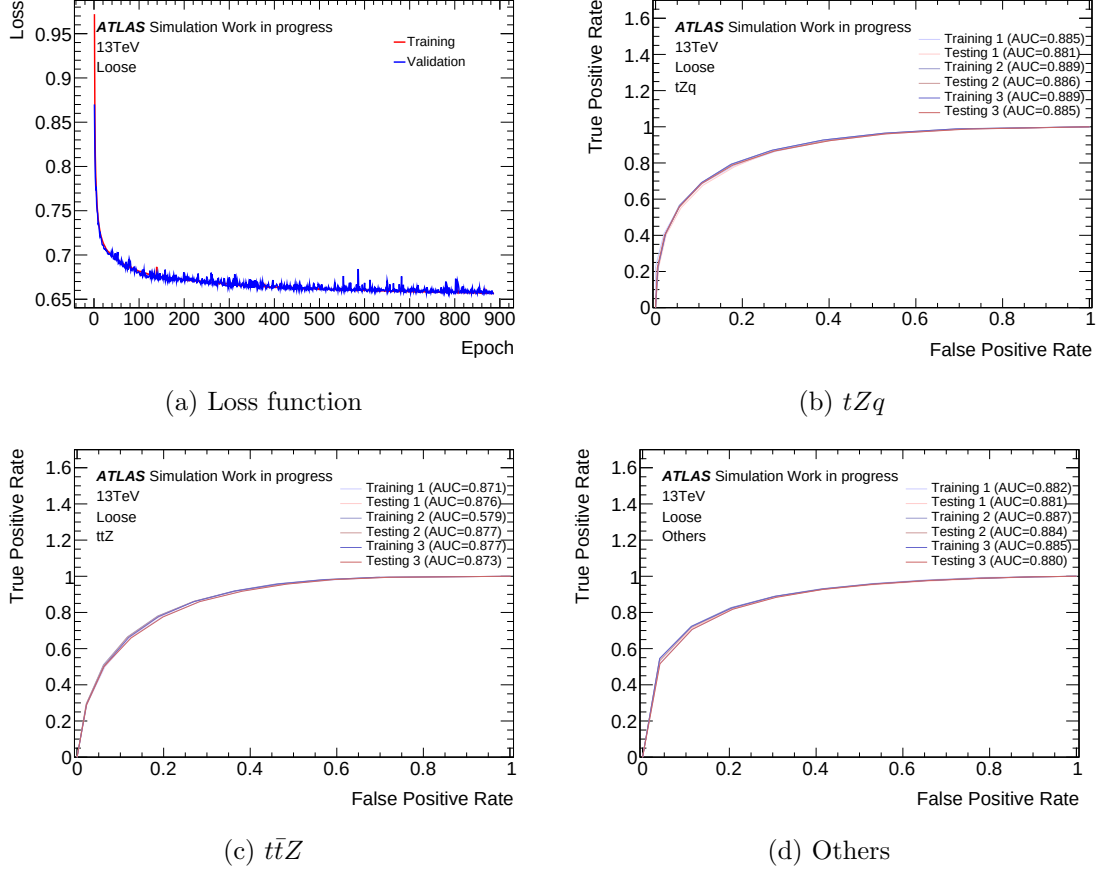


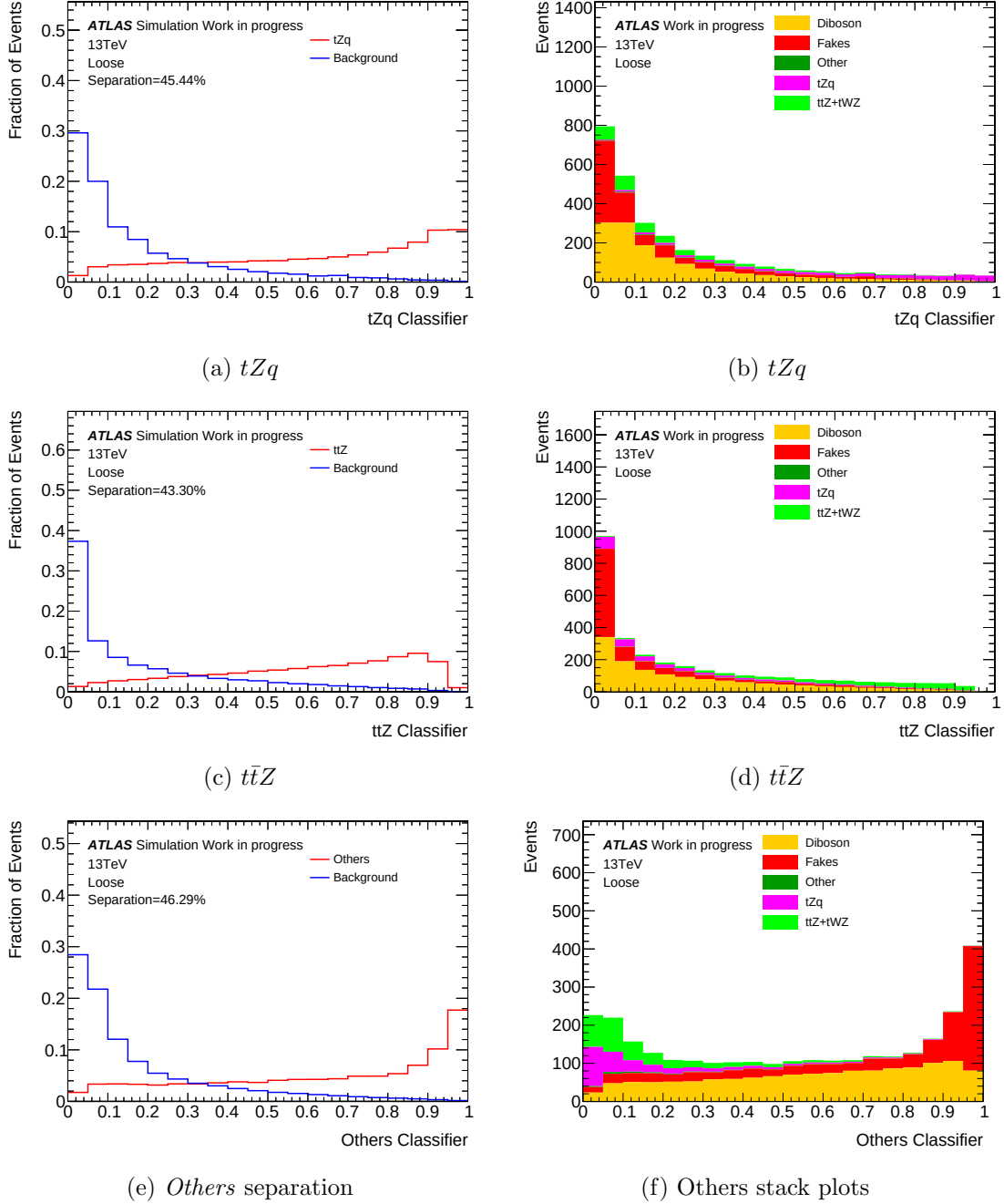
Figure 6.18: Loss function (top left) and ROC curves for tZq , $t\bar{t}Z$ and Others classifiers.

The loss function convergence was reached at around 0.66, much lower than the 1.05 of **Default**'s, and the diagonal confusion matrix elements are all above 0.70. Moreover, the ROC curves all look improved (Figure 6.18), with AUC values around 0.85, much better than **Default** (Figure 6.12).

Consequently, also the separation curves brought an improvement, with separation values rising by almost 10% with respect to **Default**, up to 45% for the signal, 43% for $t\bar{t}Z$ and 46% for Others. Especially the *Others* classifier performed best, because the target (which in this case is Fakes, Diboson and the other small contributions) distribution peaks in the last bin with almost 20% of the events. This could have been predicted since *Others* is the category with the most yields, $\simeq 2000$. The tZq classifier also peaks in the last bin for its target, however at a lower value (10%), whereas the $t\bar{t}Z$ classifier peaks earlier, around 0.85, but has the highest background contribution in the first bin, at almost 38%.

Furthermore, the stack plots on the right in Figure 6.19 give us additional information. The tZq classifier is able to perform correctly on all the backgrounds, as their distribution all peak in the first two bins. The $t\bar{t}Z$ classifier, though the one with the lowest separation, works very well on the backgrounds. In particular, almost 90% of the Fakes are located in the first bin, alongside 1/3 of Diboson and tZq . And finally, the *Others* classifier is able to peak Fakes and Diboson in the last few bins, locating signal and $t\bar{t}Z$ in the first ones as well.

Finally, in Figure 6.20 the 2D response plots and the signal significance (both $S/\sqrt{B}$ and $S/\sqrt{S+B}$) are displayed. Gathering the informations from all the plots, we can see that a signal-enriched region can be defined when $t\bar{t}Z < 0.44$ & $Others < 0.18$, because the signal is localized in the bottom left corner. $t\bar{t}Z$ instead is located mostly on the bottom right, though it is more spread in the plane than the other backgrounds, therefore a $t\bar{t}Z$ control region could be defined with $t\bar{t}Z > 0.44$, whereas the *Others*-enriched region requires $t\bar{t}Z < 0.44$ & $Others > 0.18$, since Diboson and especially Fakes are localised in the top left corner. These regions are the ones that were used for the fit described in Section 7.2.2.


 Figure 6.19: Separation curves for tZq , $t\bar{t}Z$ and *Others* classifiers.

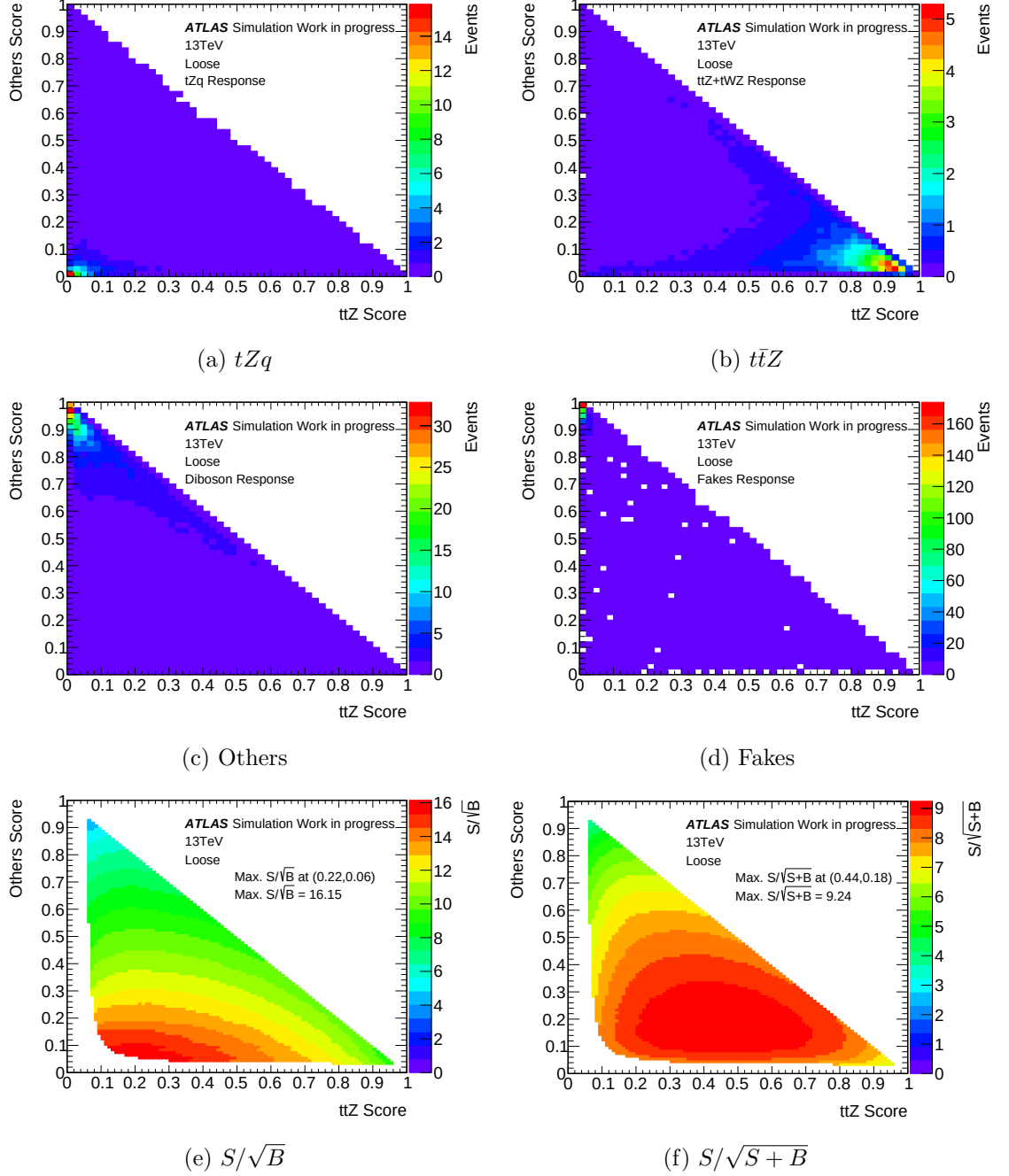


Figure 6.20: 2D response plots for tZq , $t\bar{t}Z$, Diboson and Fakes, and signal significance $S/\sqrt{B}$ and $S/\sqrt{S+B}$.

6.4 Medium selection

Finally, I will present the works done on the **Medium** selection (Table 4.5), whose yields are reported in Table 4.6. The only difference between the **Medium** and the **Loose** selection, besides the fact that the **Medium** selection includes also the *5j1b* and *5j2b* regions, is that the former has a lower threshold on $p_T(jets)$ of 25 GeV, whereas the latter has it at 20 GeV. This results in a selection with a higher signal significance than **Loose**, alongside the most signal events between the selections (326 events, 115 more than **Default**). Decreasing the jet transverse momentum threshold resulted in a decrease of the Diboson samples, especially the light component. The background which increased the most is $t\bar{t}Z$, mostly due to the *5j2b* region (as $t\bar{t}Z$ has 2 *b*-jets, and the tripletonic final state has at least 2 additional jets), resulting in 75% more yields. Finally, the Fakes background rose by 22%. Overall, the signal contribution is 11%, Diboson makes up for 40% and $t\bar{t}Z$ and Fakes account for 18% and 25% respectively.

As this selection turned out to be the most promising in terms of uncertainty on the tZq cross section, more trainings will be presented here with respect to the previous two selections. Once again, I will start describing the Binary training, followed by MC-4 and MC-3.

6.4.1 Binary

All regions together in the training

Similarly to the two previous selections, the first training was made using the simplest setup, that is a binary classifier keeping all the events together in the training. The variables used are the same 15 as the ones used in the **Loose** binary training, with the exception of a new variable, called **b1.b2_btagbin** which took the place of **bjet_btagbin**. This new variable, whose definition is credited to Thomas Stevenson, is defined as the **bjet_btagbin** of the *b*-jet if only one *b*-jet is present, whereas if 2 *b*-jets are present the variable is defined as in Equation (6.4.1), whereas Table 6.4 reports the different values that the variable can have based on the *b*-tagging scores of the two *b*-jets. This variable is used because it provides information on the second *b*-jet. Furthermore, this variable is useful on discriminating different backgrounds because Fakes and Diboson have mostly low score, whereas the high score region is occupied mostly by $t\bar{t}Z$ events, as displayed in Figure 6.21.

$$b1.b2_btagbin = (btagbin_b2 - 1) * 5 + (btagbin_b1 - btagbin_b2 + 1) \quad (6.4.1)$$

For this training, the optimised hyperparameter set was significantly different from the one obtained with the other two selection. In particular, more hidden layers were used, thus making the architecture much more complicated. Furthermore, only 10 bins were used for the NN output, in order to match the number of bins used in the bin.

- Input layers: 15 nodes (input variables)

	$\mathbf{b1} \geq 85\% \text{ (2)}$	$\mathbf{b1} \geq 77\% \text{ (3)}$	$\mathbf{b1} \geq 70\% \text{ (4)}$	$\mathbf{b1} \geq 60\% \text{ (5)}$
no $b2 \text{ (0)}$	2	3	4	5
$\mathbf{b2} \geq 85\% \text{ (2)}$	6	7	8	9
$\mathbf{b2} \geq 77\% \text{ (3)}$	10	11	12	13
$\mathbf{b2} \geq 70\% \text{ (4)}$	14	15	16	17
$\mathbf{b2} \geq 60\% \text{ (5)}$	18	19	20	21

Table 6.4: Different values that the `b1.b2.btagbin` variable can have, based on the score of the two jets. Between brackets the `btagbin` value associated to the score is reported.

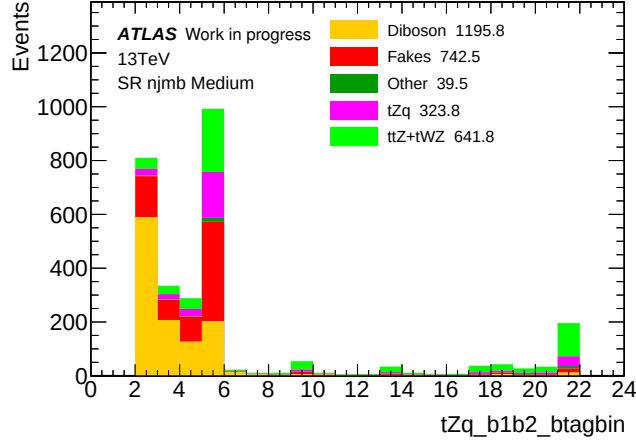


Figure 6.21: `b1.b2.btagbin` distribution

- 5 layers
- Nodes in each layer: 70, 70, 40, 50, 70
- Activation functions: *ReLU*, *ReLU*, *ReLU*, *ReLU*, *ReLU*
- Batch size = 1000
- Learning rate = 0.0005
- Dropout rate = 0.3 on layers 0,1,2,3
- No batch normalisation layers
- 3 folds for cross-validation

In spite of having more input data, because the total yields are more than they were for the `Loose` selection, the NN performance was deteriorated a bit. This is caused by the fact that events with a different jet multiplicity were included in the trainings. The outcome of this is displayed in the loss function and in the ROC curve (Figure 6.22). The convergence value of the loss function is reached at 0.43, to be compared with 0.40

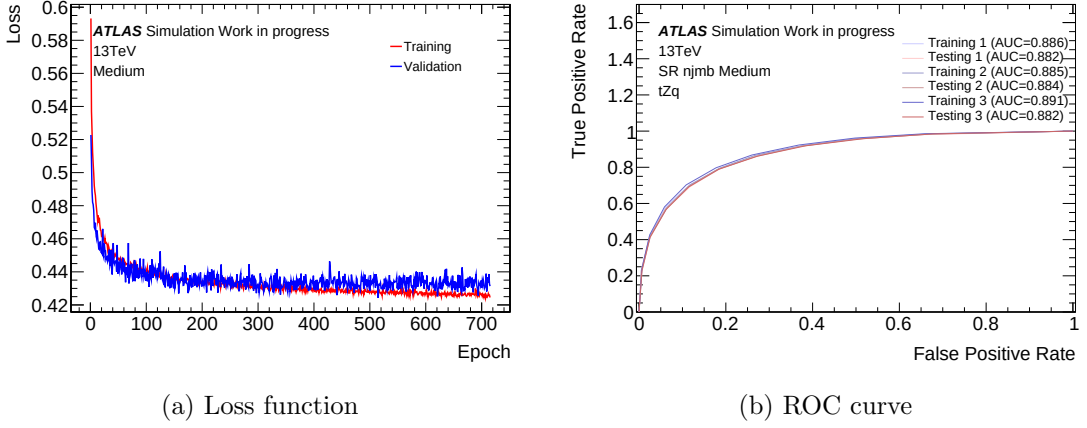


Figure 6.22: Loss function (left) and ROC curve (right) for the Binary training.

obtained with the **Loose** binary training, and the AUC values are a bit lower too (0.88 on average, versus 0.89 for **Loose**). On the contrary, the diagonal matrix elements are the same on average.

Additionally, I am presenting also the input variables ranking, in Figure 6.23. We can see how the highest ranked variables are the ones containing information about the forward jet j_f . Moreover, we can see that the charge of ℓ_W , multiplied to its p_T , is ranked third in the ranking, with an impact of 16%. This will turn useful once the *top* and *antitop* quark contributions are split, as will be presented in Section 7.3.

The training deterioration is displayed also by the separation and the stack plot (Figure 6.24). The total separation decreased from 47% to 45%, as the background contribution for output values greater than 0.5 is almost 20%. Nevertheless, this trainings have almost 25% of the total signal events in the last bin as well, hence confirming that this training, though worse than the other one, is still much better than **Default** and could bring good results with the fit.

Regarding the backgrounds, Fakes and Diboson are treated best, as their distributions peak in the first and second bin respectively. However, the tZq classifier was not able to treat $t\bar{t}Z$ as good, since its distributions peaks in the fourth bin. In spite of this, the last bin has almost 4.5 times more signal than background, with a signal significance $S/\sqrt{S+B}$ of 8.

Overall, although this training performed slightly worse than the **Loose** training, we expect the fit to return a lower signal strength uncertainty. This is due to the fact that this selection has much more signal yields, thus improving the overall fit performance. We will see these results in Section 7.2.3.

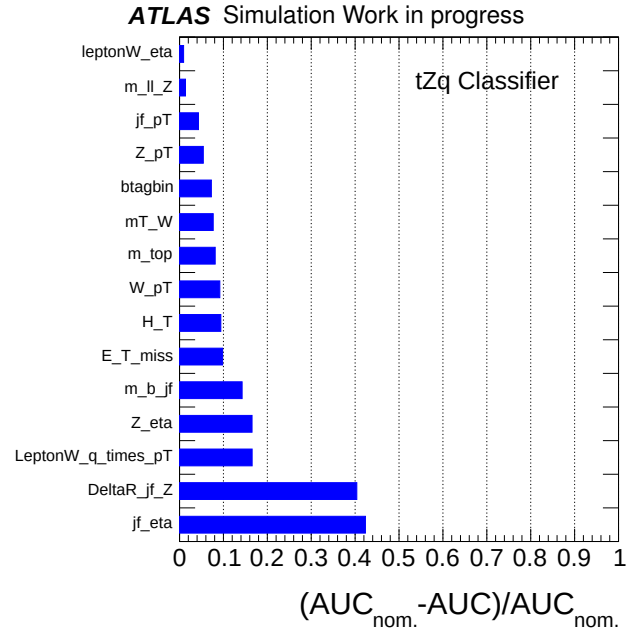


Figure 6.23: Input variables ranking for the Binary NN training with the **Medium** selection.

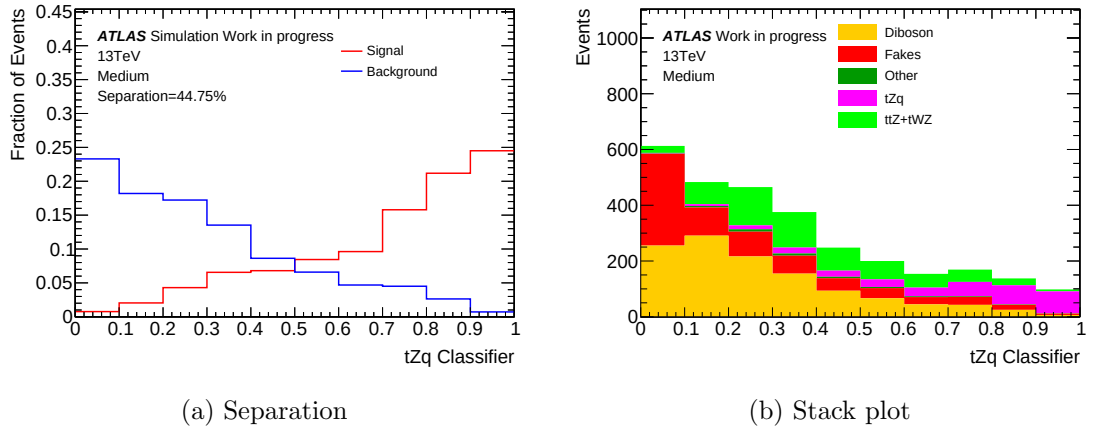


Figure 6.24: Separation (left) and stack plot (right) for the Binary training.

Splitting regions in the training

Similarly to what was done for the `Default` selection, we decided to perform a binary training splitting the events based on the jet multiplicity. This time however, the whole dataset was split in three regions: regions without j_r (`no-RJ`; $2j1b$ and $3j2b$), regions with j_r and 1 b -jet (`RJ-1b`; $3j1b$, $4j1b$ and $5j1b$), and finally regions with j_r and 2 b -jets (`RJ-2b`; $4j2b$ and $5j2b$). The yields are reported in Table 6.5.

Samples	no-RJ	RJ-1b	RJ-2b
tZq	136.2 ± 29.8	143.7 ± 21.2	46.4 ± 10.9
$VV + b$	115.3 ± 4.1	131.7 ± 4.4	21.9 ± 0.8
$VV + c$	242.1 ± 8.4	268.8 ± 8.8	13.4 ± 0.5
$VV + l$	191.9 ± 6.6	215.8 ± 7.4	4.1 ± 0.2
$t\bar{t}Z$	112.7 ± 10.5	239.2 ± 10.6	197.9 ± 10.0
$t\bar{t}W$	10.3 ± 0.4	7.0 ± 0.3	4.6 ± 0.2
tWZ	24.2 ± 3.0	54.4 ± 7.8	18.5 ± 4.9
$t\bar{t}H$	4.4 ± 0.2	7.0 ± 0.2	6.1 ± 0.2
Fakes	428.9 ± 29.1	302.7 ± 18.7	25.7 ± 2.4
Other	0.0 ± 0.0	0.1 ± 0.0	0.2 ± 0.0
Total	1266.0 ± 58.4	1370.3 ± 52.3	338.9 ± 18.2

Table 6.5: Event yields for the three regions used for the training.

The inclusion of the 5 jets regions allowed us to have enough statistics to train separately two RJ regions, splitting them based on b -jet multiplicity. This additional splitting helps us because the $2b$ -jets region is mostly made of $t\bar{t}Z$ (more than 50%), with a signal, Diboson and Fakes contributions of 14%, 11% and 8%, respectively. On the other hand, the $1b$ -jet region has the most contributions coming from Diboson (45%) and Fakes (22%), with $t\bar{t}Z$ (17%) and signal (11%) being less present. Therefore, the two regions are very different in background composition, hence justifying the use of two separate trainings. Nevertheless, the low statistics in the `RJ-2b` region will result in a worse training than the other two.

For the `no-RJ` region, the highest contribution comes from the $2j1b$ region, whose total yields are 1082, more than 85% of the total in the region, of which 101 signal events (74% of the total tZq events in the region). Consequently, this will be the region for which the training will perform better, since the yields are high and the region is made up of almost only one jet multiplicity region.

The variables used for the trainings are the same ones used in the Binary training above, with the addition of the radiation jet variables $|\eta(j_r)|$ and $p_T(j_r)$ in the two regions with a *radiation jet*, the number of jets in all the regions and finally the number of b -jets only in the `no-RJ` region, since in the other two regions the number of b -jets is fixed.

More than 4000 different configurations were tested for the hyperparameter optimisation, which produced a very different set with respect to the previous trainings, which

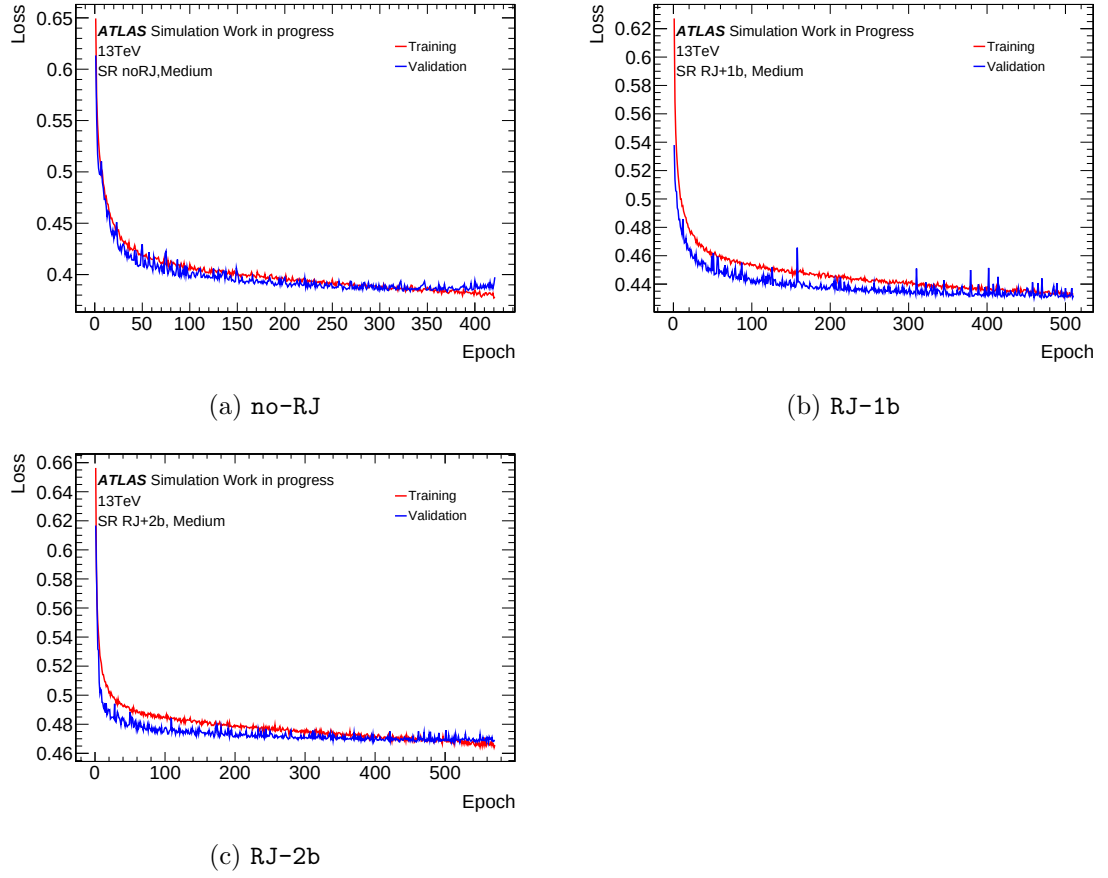


Figure 6.25: Loss curves for the 3 trainings.

is presented in Table 6.6.

Figures 6.25 and 6.26 display exactly what we expected. The loss function for no-RJ reaches the lowest convergence among all the trainings displayed above, at 0.38. The AUCs

Hyperparameter	no-RJ	RJ-1b	RJ-2b
Input layers	16	17	17
Hidden layers	3	3	3
Nodes	80, 80, 80	80, 80, 80	80, 80, 80
Activation functions	<i>eLu</i> , <i>eLu</i> , <i>eLu</i>	<i>eLu</i> , <i>eLu</i> , <i>eLu</i>	<i>eLu</i> , <i>eLu</i> , <i>eLu</i>
Batch size	5000	2000	5000
Learning rate	0.001	0.0005	0.001
Dropout rate	0.2	0.2	0.2
Dropout layers	0,1,2,3	0,1,2	0,1,2
Batch normalisation layers	1,2,3	1,2,3	1,2,3
Number of folds	4	4	4

Table 6.6: Optimised set of hyperparameters used in the trainings.

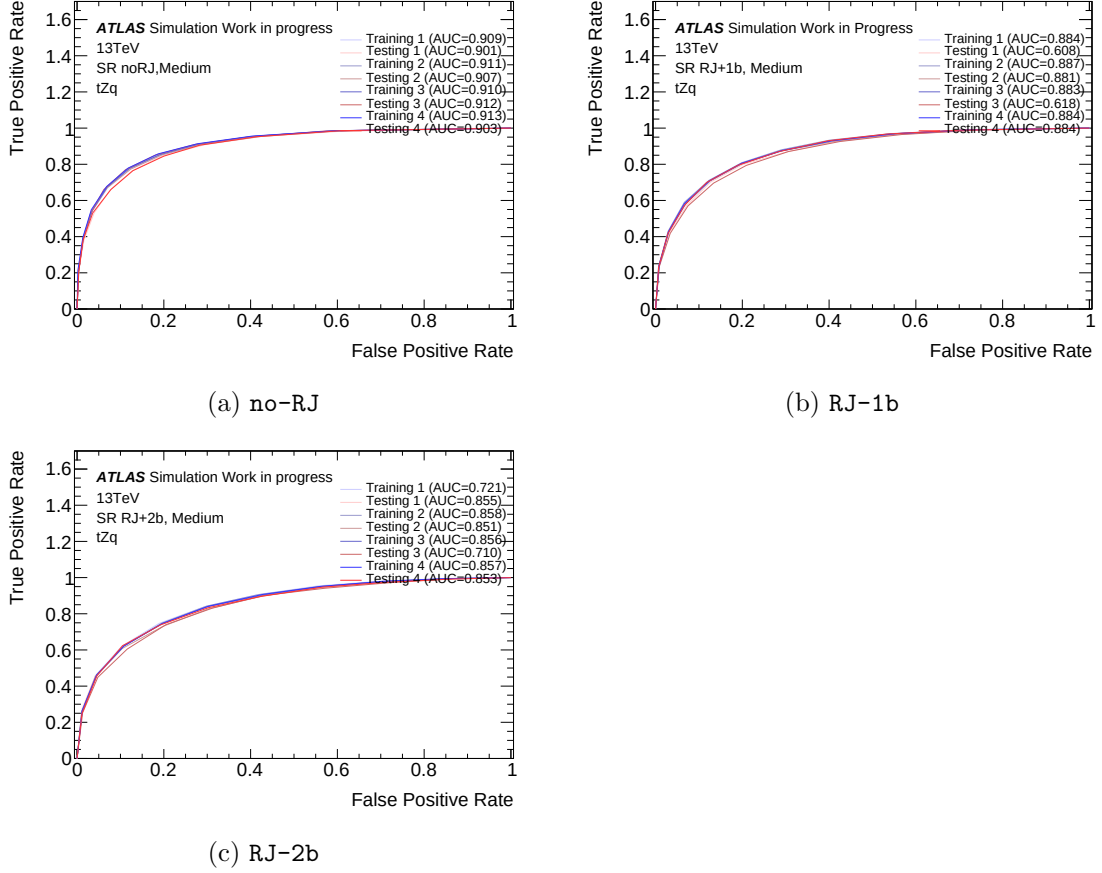


Figure 6.26: ROC curves for the 3 trainings.

are the best ones yet, being all above 0.90, and the confusion matrix diagonal elements are the highest ones as well (0.82 and 0.83). As aforementioned, this is due to the region being almost completely made of $2j1b$.

In contrast, the RJ-1b training performance is slightly deteriorated. The training converges to a value of 0.42, still better than the RJ training of `Default` selection and the Binary training shown above with this selection. The AUCs are in general good (with the exception of two training AUCs with values of 0.6, which however do not affect too much the overall training), with an average of 0.88, slightly lower than the Binary training with all regions together. Likewise, the confusion matrix diagonal elements are almost the same of the Binary with all regions, around 0.80.

Finally, the RJ-2b region is the worst training among the three, as the statistics is very limited. Nevertheless, this training turned out to be better than expected. The loss function converges at around 0.47, the AUCs are all but two above 0.85, and the confusion matrix elements are 0.79 and 0.75, similar to the values of the RJ training with the `Default` selection.

Separation and stack plots (Figure 6.27) confirm the considerations made above. The no-RJ is the training with the highest separation, 51.3%. It stands above all other

trainings especially for its ability to have more than 40% of the signal in the last bin, with less than 10% being in the regions with $O_{NN} < 0.5$. The backgrounds instead follow the exact opposite pattern, with 40% of them in the first bin and less than 10% in the last bin. The signal contribution in the last bin is almost 3 times the background's, and the highest signal significance is obtained in the second-to-last bin with $S/\sqrt{S+B} = 6.90$. As far as the distributions are concerned, the NN is able to classify correctly all backgrounds. Both Diboson and Fakes peak in the first bin, with the latter especially having more than 50% of its total events in there. The NN's performance on $t\bar{t}Z$ is not as good, because $t\bar{t}Z$ has less statistics in this region, but it is still able to have it peak in the third bin. All in all, this is the best NN trained in this thesis.

The **RJ-1b** training instead worked a bit worse, as expected. Nonetheless, the NN is able to place 30% of signal and backgrounds in the last and first bin, respectively. This is better than the binary trained with all regions together (Figure 6.24(a)), in spite of the total separation being slightly lower (44% versus 45%). 25% of the signal events are found in the first 5 bins, more than twice than the **no-RJ** training, and the same figure is found for the backgrounds in the last 5 bins. Even so, all background distributions peak in the first bin, with the exception of $t\bar{t}Z$ which peaks in the second, whereas in the last bin the signal is 2.5 times more than the backgrounds.

Finally, the worst training out of the three is **RJ-2b**. This training's separation is 37.5%, comparable with the **RJ** training with the **Default** selection (Figure 6.9). Of particular significance is the fact that all background sources peak in the second bin, thus ensuring a non perfect training. Nevertheless, the signal distribution looks fine, with 30% of the signal in the last bin and a signal/background ratio in the last bin of 3.3.

The fit which uses these three regions is presented in Section 7.2.3.

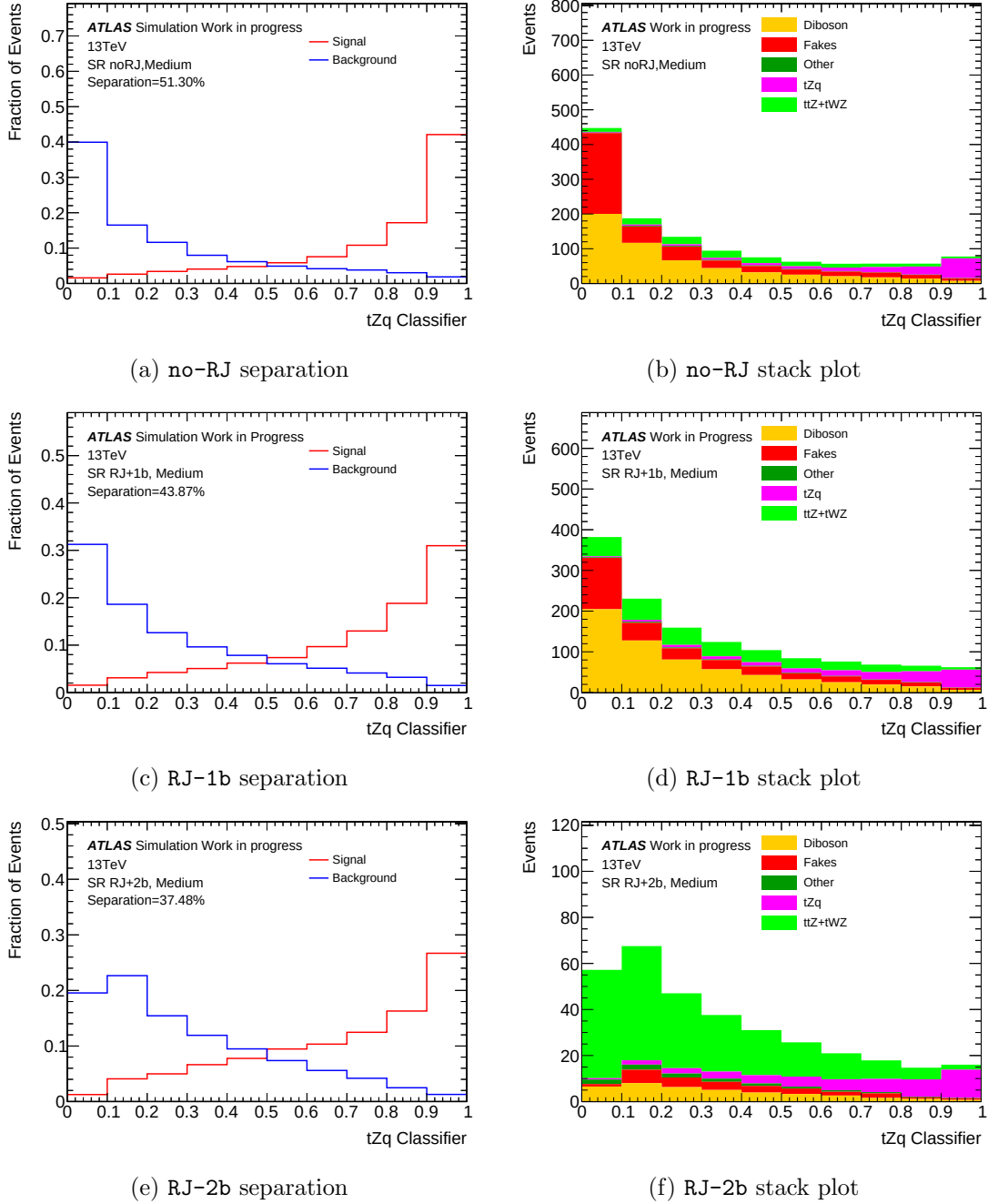


Figure 6.27: Separation plots (left) and stack plots (right) for the 3 different classifiers.

6.4.2 Multi Class: 3 classes

Following the steps taken for the previous two selections, a Multiclass NN was tested. Both a MC-3 and MC-4 trainings were performed, but here I will present only results from the former, since the latter turned out to be worse for the fit.

Additionally, for this NN setup we decided to test a different set of variables, called *Lorentz invariant variables*. These variables differ from the *Standard variables* used so far because they hold the property of being scalars under Lorentz transformations. The variables used are either “standard” variables which are Lorentz invariant (such as invariant masses), or they are scalar products of “standard” variables, with the scalar product defined in the Minkovsky space-time as $x_\mu y^\mu = x_0 y_0 - \vec{x} \cdot \vec{y}$.

The idea behind this test is to evaluate whether a training with these variables performs better or worse than a training with the standard variables. In view of a differential cross-section measurement, the attempt was to try to have a NN discriminant built from variables that are the least correlated with the variables with respect to which the differential measurement will be performed. Therefore, two different multiclasss have been tested, one with $t\bar{t}Z$ as target and one with VV , and these MCs were then trained both with standard and Lorentz invariant variables. Then, a fit was made to both MCs, in order to have a comparison.

I will begin this section by presenting the Lorentz invariant variables trainings, and then I will continue with the standard variables.

Lorentz invariant variables: Diboson

To begin with, I will present the Lorentz invariant training for a multiclass with signal, VV and Others as the targets. The variables used are reported in Table 6.7.

For this training, a more complex set of hyperparameters was returned from the optimization.

- Input layers: 13 nodes (input variables)
- 5 layers
- Nodes in each layer: 70, 70, 40, 50, 70
- Activation functions: tanh, *ReLU*, sigmoid, tanh, sigmoid
- Batch size = 2000

$\ell_W \cdot b_j$	$\ell_W \cdot j_f$	$\ell_1^Z \cdot b_j$	$\ell_1^Z \cdot j_f$	$\ell_1^Z \cdot \ell_W$
$\ell_2^Z \cdot b_j$	$\ell_2^Z \cdot j_f$	$\ell_2^Z \cdot \ell_W$	b1_b2_btagbin	$m_T(W)$
$m(b, j_f)$	$m_{\ell\ell}$	m_{top}		

Table 6.7: List of Lorentz invariant variables used in the training. The “.” denotes a scalar product

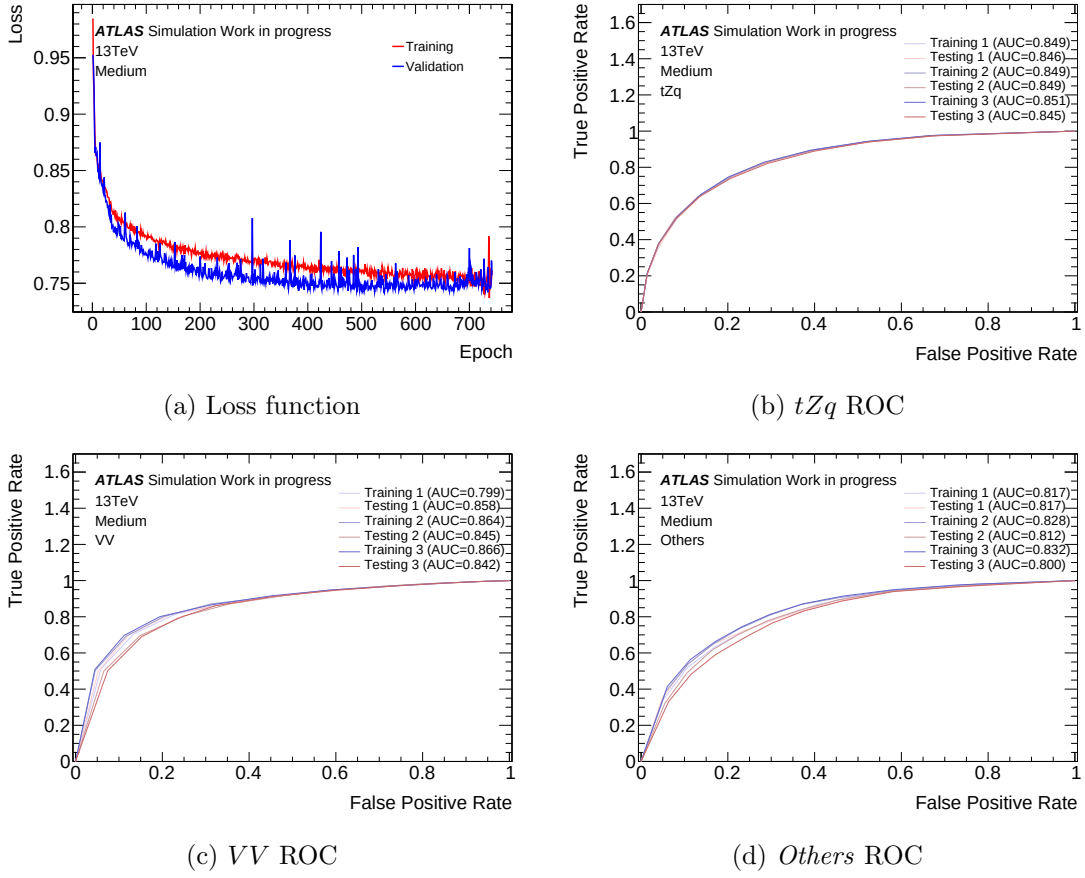


Figure 6.28: Loss function (top right) and ROC curves for the three classifiers

- Learning rate = 0.0005
- Dropout rate = 0.3 on layers 0,1,2,3
- No batch normalisation layers
- 3 folds for cross-validation

The training outcome was a bit worse than the Loose MC-3 training shown in Section 6.3.2. The loss function convergence is reached at 0.75, whereas the other training had a convergence at 0.68. Moreover, the loss function displays some fluctuations, which might indicate a non perfect training, even though this was the best setup from the hyperparameter optimisation. The matrix elements are quite low, with the *Others* elements being the lowest, at 0.59. Additionally, the ROC curves are significantly worse than the other MC-3 training, as can be seen in Figure 6.28, where it is clear how the *Others* classifier is the worst out of the three.

In Figure 6.29 the three separations are presented, and they immediately look worse than the ones for the Loose selection (Figure 6.19). The best separation value is obtained for the *VV* classifier at 39%, followed by *tZq* and *Others*, at 37 and 29%, respectively.

Nonetheless, all three classifiers were able to locate more than 40% of the backgrounds in the first bin, but they were never able to peak their target distributions in the last bin. The stack plots reflect these issues, because, in spite of rightfully treating all the backgrounds, the target of each classifier never peaks in the final bin. In particular, the *Others* classifier is almost flat on $t\bar{t}Z$ up until an output of 0.8, where it then drops suddenly, ending up with a negligible contribution in the final bin, which in turn is dominated by the Fakes.

Similar to what was done for the **Loose** selection for the MC-3 classifier, we tried to define regions by using the 2D response plots. However, this classifier did not allow for creating regions. The $t\bar{t}Z$ response is almost flat in the *Others* classifier, with also a small peak close to $VV = 1$. The signal response is too spread to generate a pure signal-enriched region, also because in what would be the signal region, the $t\bar{t}Z$ contribution would be quite high. Only Diboson and Fakes were well located in the corners of their respective classifiers.

Therefore, the fit was made using only a signal region, in which the tZq classifier was fit, and the results will be presented in Section [7.2.3](#).

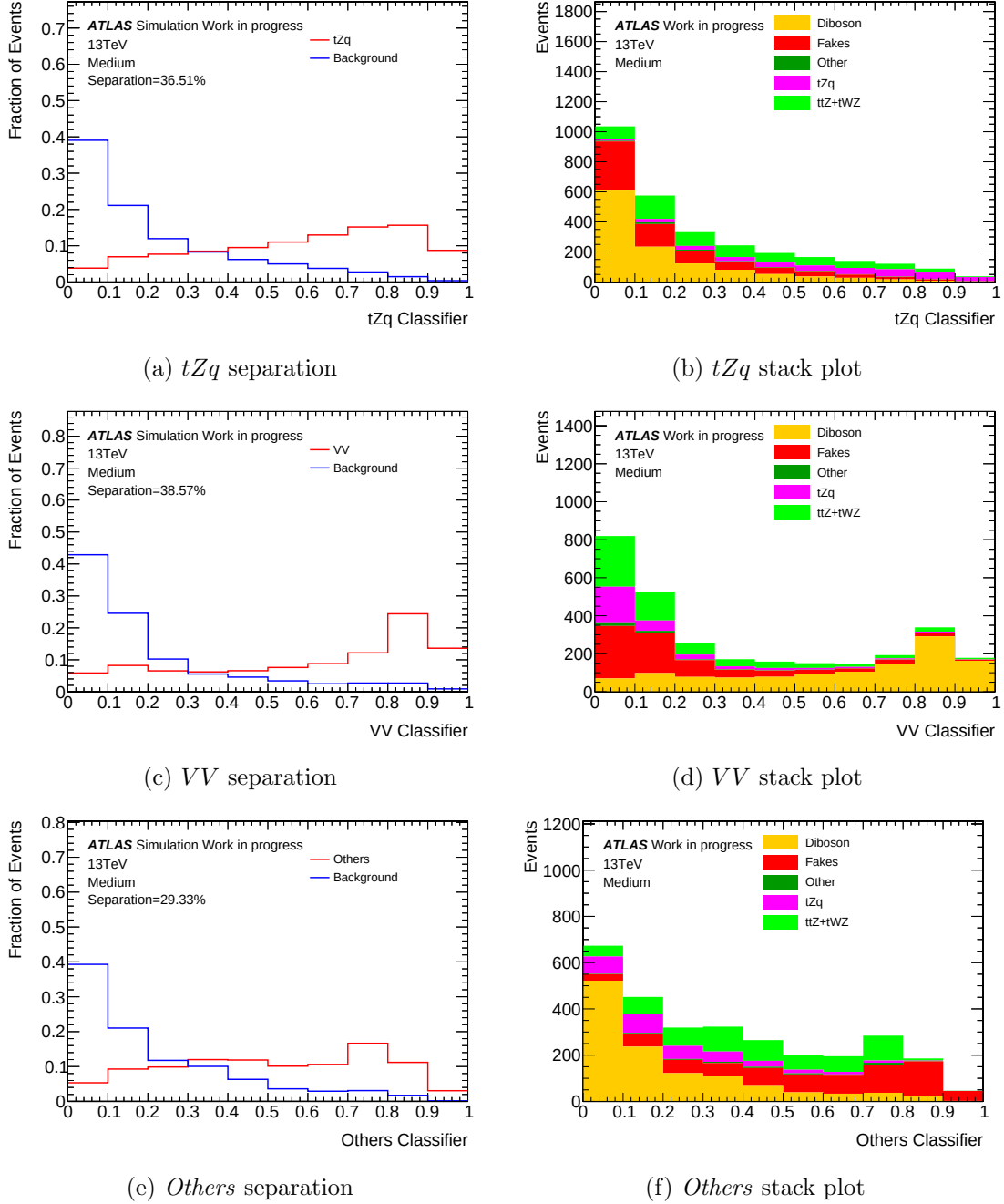


Figure 6.29: Separation curves (left) and stack plots (right) for the three classifiers

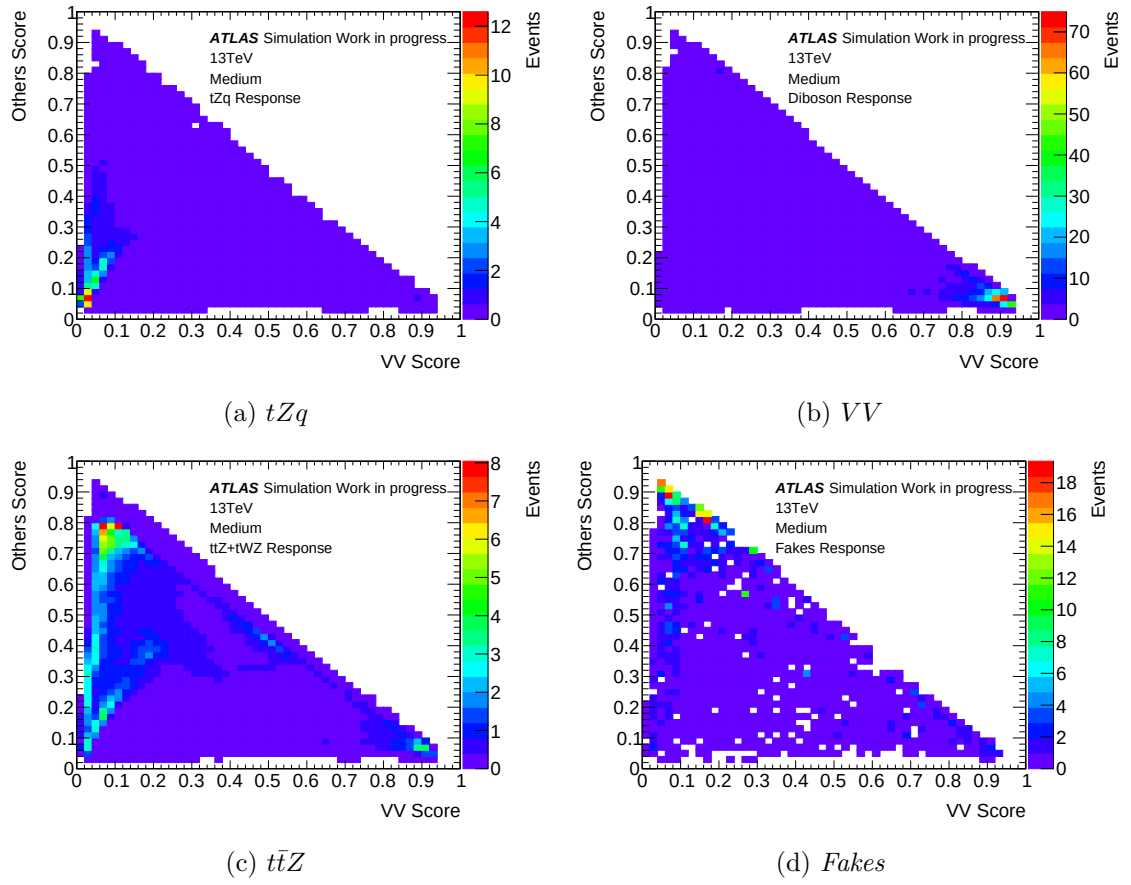


Figure 6.30: 2D response plots in the Diboson vs *Others* classifier plane

Lorentz invariant variables: $t\bar{t}Z$

Similarly, the same variables were used to train a multiclass NN with Signal (0), $t\bar{t}Z$ (1) and *Others* (2) as targets. The hyperparameters from the optimisation are similar to the ones of the *VV* MC, with the exception of activation functions, where *ReLU* was used on all hidden layers, and learning rate, which was increased to 0.001.

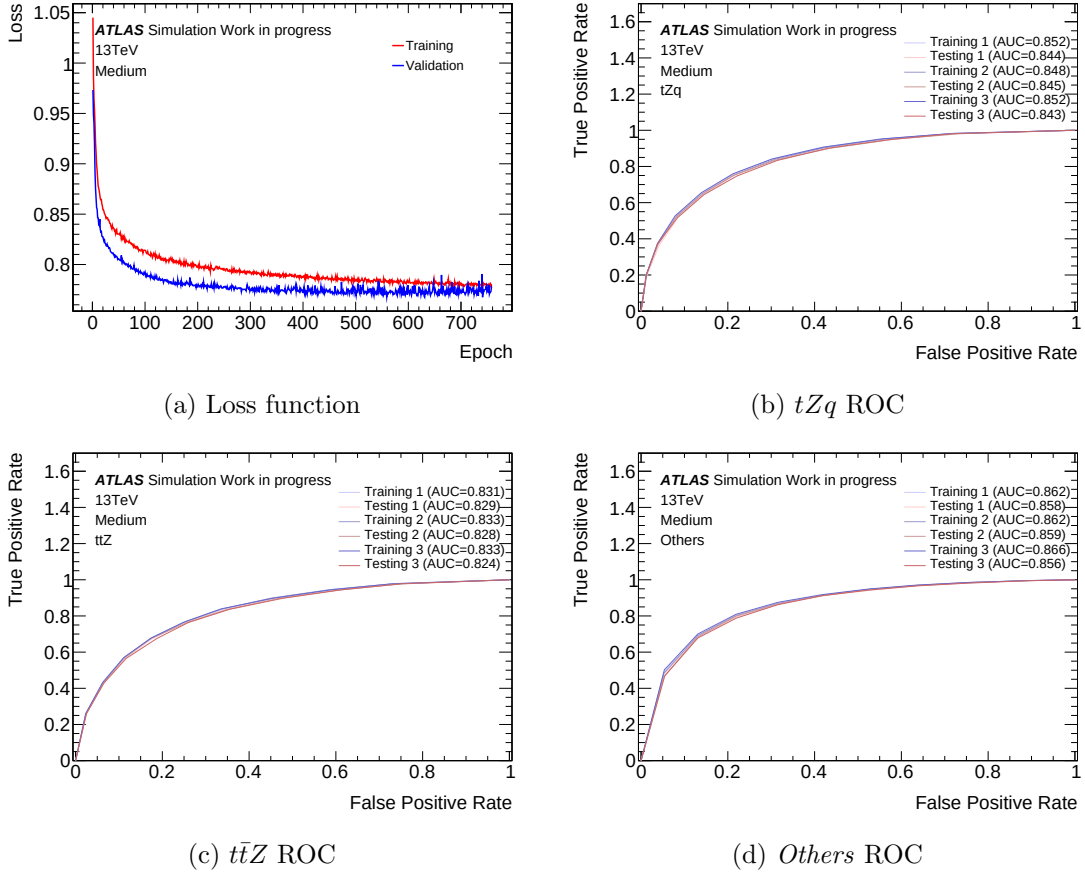


Figure 6.31: Loss function (top right) and ROC curves for the three classifiers

Overall, this training performed worse than the MC-3 *VV* just presented. The loss function (Figure 6.31(a)) reaches a higher convergence (0.77) than the *VV* training (0.75). The AUCs instead are similar for tZq (both around 0.85), significantly worse for $t\bar{t}Z$ (0.83, to be compared with *VV* at 0.86) and in turn significantly better for *Others* (0.87 versus 0.82). In conclusion, the ROC curve test did not give any significant remarks. However, the confusion matrix displays a substantial deterioration, because the tZq and $t\bar{t}Z$ diagonal elements are both below 0.65, to be compared to the 0.71 of the *VV* trainer. Only the *Others* matrix element showed an improvement, going from 0.59 to 0.74.

As expected, separation values (Figure 6.32) are lower for the tZq and the $t\bar{t}Z$ classifiers than they were in the MC-3 *VV* NN. The signal distribution is almost flat, with a small peak at 0.7 and a drastic drop in the last bin, where less than 2% of the signal

events are found. A similar outcome is observed for the $t\bar{t}Z$ classifier, where there are no $t\bar{t}Z$ events in the last bin. On the contrary, the *Others* classifier worked better than it did with the VV multiclass. The separation increased from 29% to almost 40%, thus making it the best classifier in the Lorentz-invariant-variables-category. Nevertheless, this classifier did not correctly treat the VV background, which peaked at 0.8, thus leaving the final bin to the Fakes only.

The 2D response plots (Figure 6.33) tell the same story. The tZq response is even more spread than it was for the VV MC-3, as well as Diboson. The fakes instead are found once again the top left corner, thus meaning that their training was executed correctly, whereas $t\bar{t}Z$, which should have been well localized since it is one of the targets, is quite spread, since, as the stack plots told us, its distribution is quite flat. Therefore, even for this training different regions for the fit could not be defined, as the fit in Section 7.2.3 will show.

All these differences were to be expected, because the Lorentz invariant variables do not provide a prior separation as good as the standard variables. For instance, the distribution of $|\eta(\ell_W)|$ (a standard-variable) is flat for backgrounds where a W boson is not present, such as Fakes or $t\bar{t}Z$, whereas it has a non-trivial distribution for Diboson (because of WZ) and signal, because a W boson is present. Similarly, all the other standard variables have a peculiar shape for each sample which helps the NN on separating the different sources. On the contrary, the Lorentz invariant variables do not carry this property, because the physical meaning of the variable is lost. Additionally, these variables range for multiple orders of magnitude. Therefore, since the NN rescales all the variables such that their values are in the 0-1 range, it can become hard to translate the properties after the rescaling, because the rescaled variables look like the one in Figure 6.34(b). On the other hand, the standard variables distributions display the different shapes of the distributions, even after rescaling, as shown by Figure 6.34(a).

Consequently, because the different shapes of each sample are not used at best in the training, the NN cannot use this property for the training and thus bases its results mostly on the statistics given. Therefore, a MC-3 training in which VV is one of the outputs is expected to perform better than a MC-3 with $t\bar{t}Z$ because the Diboson component is greater than that of $t\bar{t}Z$. And it also makes sense that the *Others* classifier is better in the MC-3 $t\bar{t}Z$ because the *Others* target is made of Fakes and Diboson, thus having more yields than the *Others* target in the MC-3 VV training. This outcome is the opposite of what is observed when using the standard variables, where the different shapes of the input variables allow for a multiclass with $t\bar{t}Z$ as output to perform better than a multiclass with VV as output, as I will show right below.

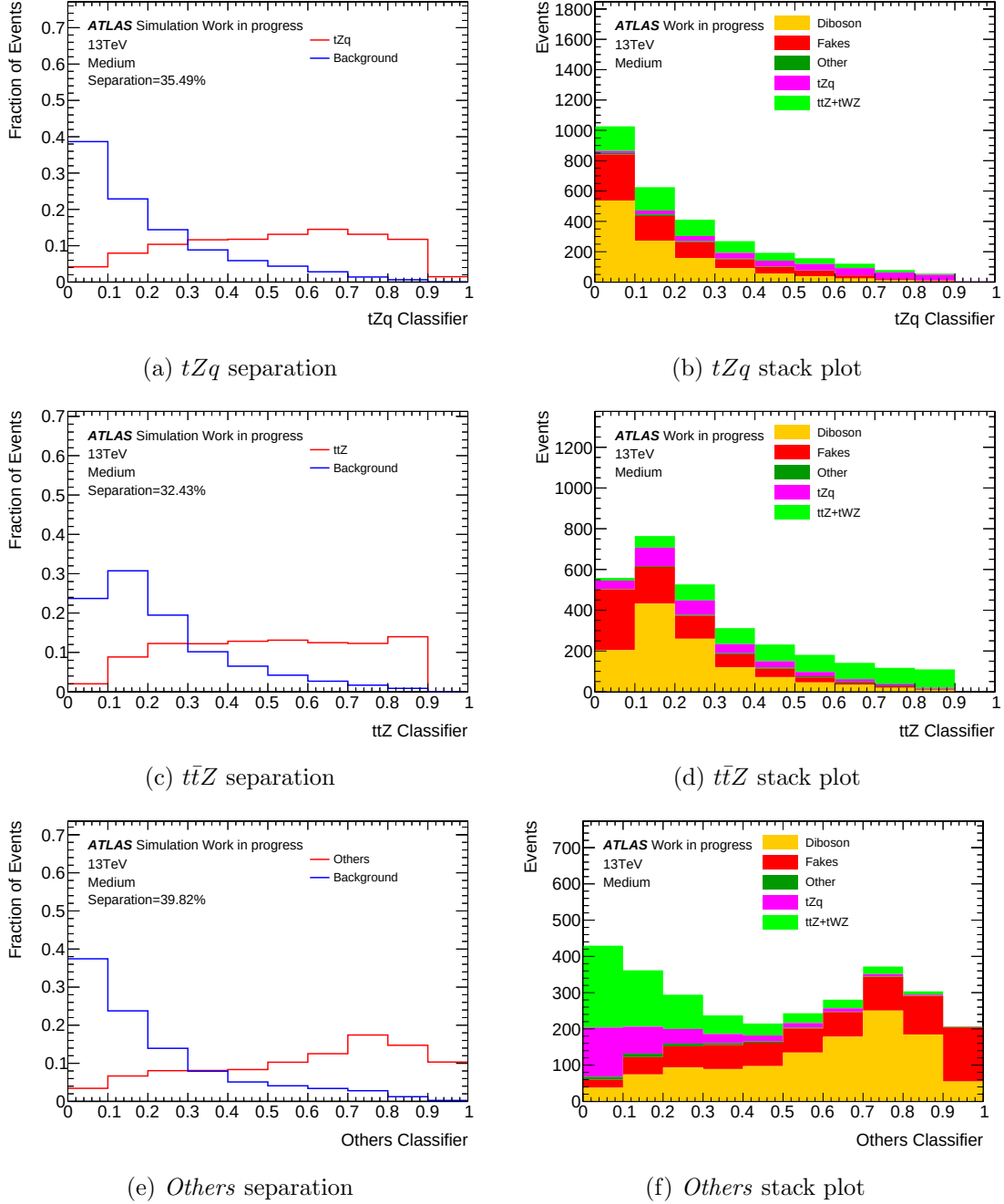


Figure 6.32: Separation plots (left) and stack plots (right) for the three classifiers

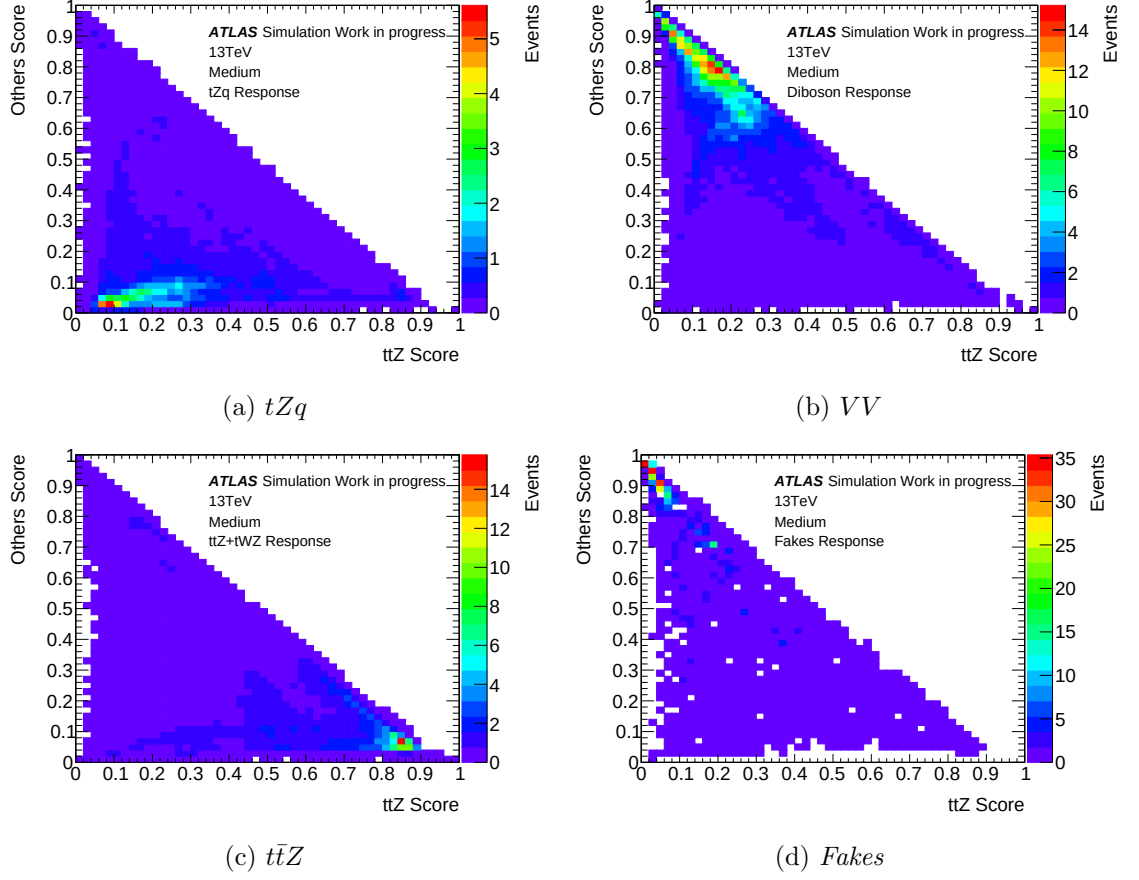


Figure 6.33: 2D response plots in the $t\bar{t}Z$ vs *Others* classifier plane

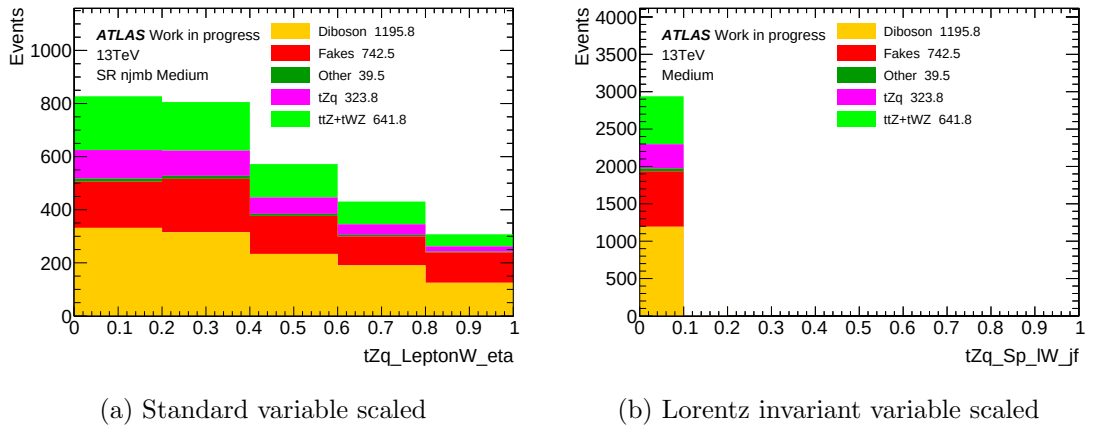


Figure 6.34: Comparison between a scaled standard variable (left) and a scaled Lorentz invariant variable (right).

Standard variables: Diboson

After performing the tests with the Lorentz invariant variables, we returned to using the standard variables for all remaining trainings, in order to make comparisons between the two. Therefore, the first training is a Multi Class with tZq (0), VV (1) and $Others$ (2) as outputs. The standard variables used are the same as the ones used in the Binary training, whereas the hyperparameter set from the optimisation is the same as the Lorentz invariant variables, with the exception of a greater batch size (5000 instead of 2000), a lower dropout rate (0.2 instead of 0.3), which is not applied on the third layer, and one less fold (3) used for cross-validation.

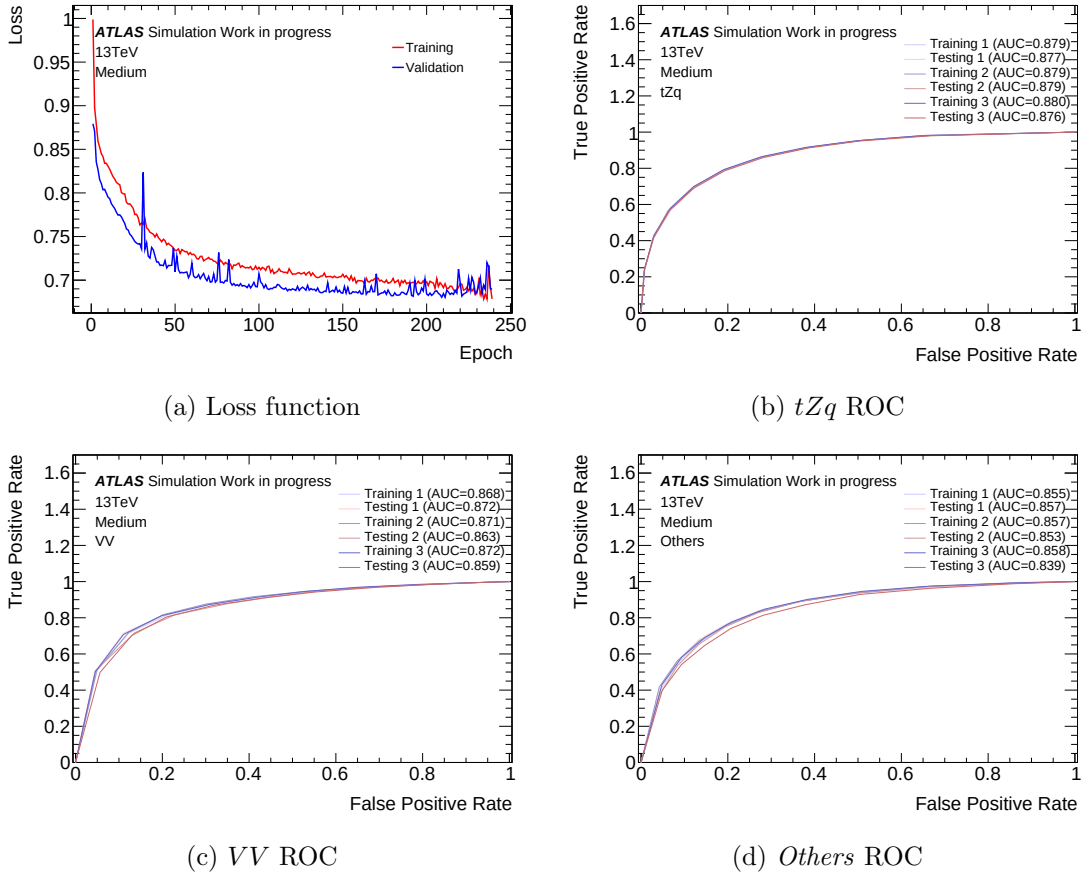


Figure 6.35: Loss function (top right) and ROC curves for the three classifiers

The performance of this training is improved with respect to Lorentz invariant variables. The loss function converges at 0.68, almost 0.1 lower than the other one. Moreover, all AUCs are on average greater, as well as confusion matrix diagonal elements. These results validate the supposition that standard variables perform better than Lorentz invariant variables.

Consequently, we observe higher separation values for all three classifiers (Figure 6.36). The signal reaches a 44% separation, being able to locate almost half the backgrounds in

the first bin and more than 20% of the signal in the last, where its distribution peaks and where there is 4 times more signal than backgrounds. Moreover, Diboson and Fakes all peak in the first bin, whereas only $t\bar{t}Z$ peaks in the second one.

The Diboson classifier has a 42% separation, increased by 10% with respect to the Lorentz invariant variables training, and, in spite of its target's distribution peaking in the second to last bin, where almost 30% of the total events are found, it is able to correctly treat all other sources, since they all peak in the first bin.

Finally, the *Others* classifier is the one with the greater improvement with respect to the previous Lorentz invariant training. The separation is increased from 29% to 37.5%, the distribution is not as flat as it was in Figure 6.29(e), with a peak in the second to last bin, which is then not followed by a sudden drop in the last bin, where we can still find around 8% of the total *Others* sources.

Nevertheless, the greater advantage of using the standard variables comes from the 2D response plots, displayed in Figure 6.37. From these plots, it is possible to define different regions in which a single background component is present, something which was not possible with the Lorentz invariant variables. The signal is located all in the bottom left corner of the VV -*Others* plane, thus allowing for a signal-enhanced region to be defined in order to maximise the signal significance $S/\sqrt{S+B}$ at $VV < 0.24$ and $Others < 0.29$. A Diboson-enhanced region can be defined by locating the bottom right corner of the plane, with $VV > 0.24$ and $Others < 0.29$, because Diboson is localized all in the high- VV region, whereas the *Others*-enhanced (Fakes and $t\bar{t}Z$) region is the region orthogonal to the previous two, hence with $Others > 0.29$. In this region, almost all the Fakes are included, because they all are located in the high-*Others* region, whereas $t\bar{t}Z$, in spite of being more spread in the plane, still has the majority of events in that region.

These regions were later on used for the fit, described in Section 7.2.3

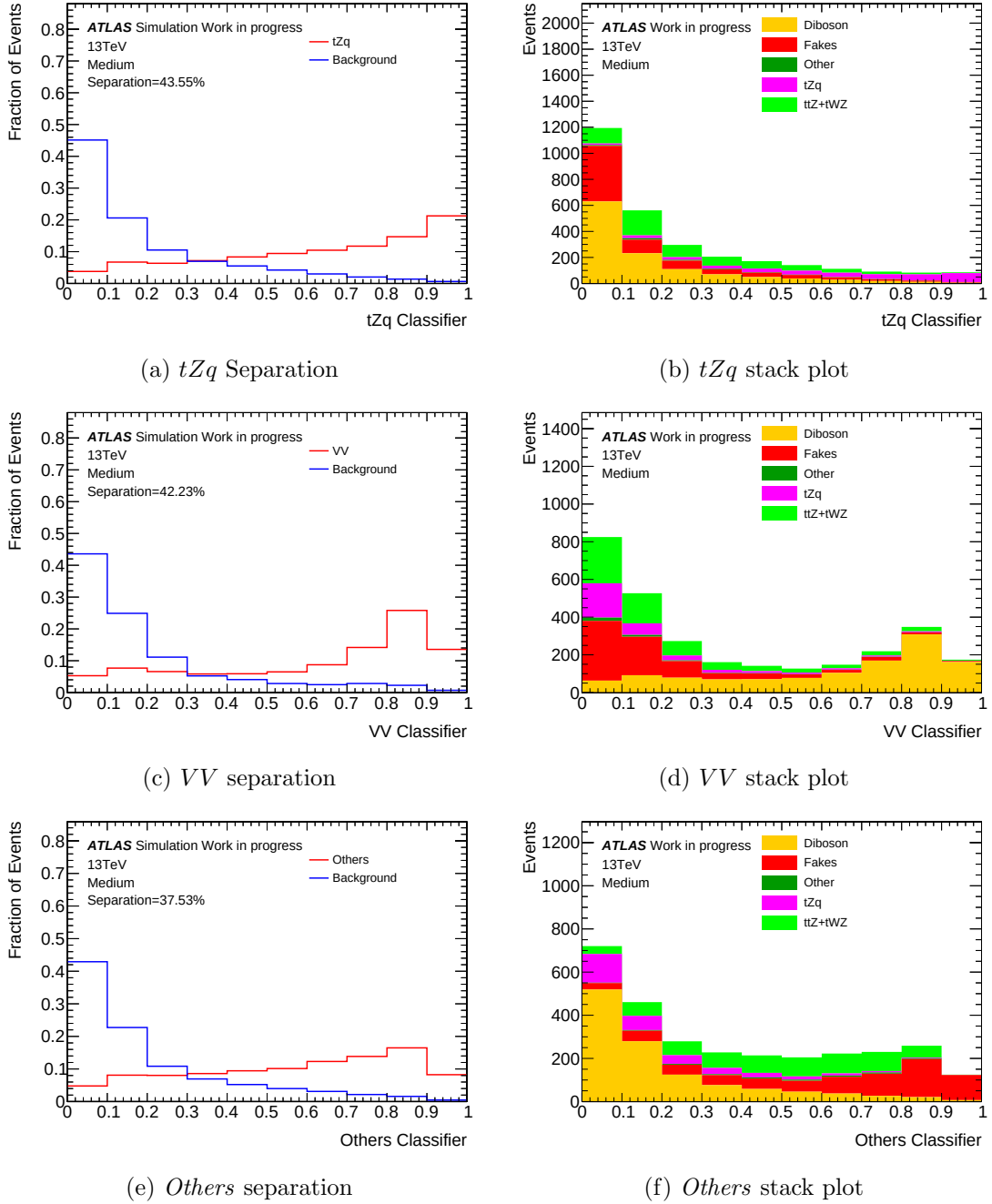


Figure 6.36: Separation curves (left) and stack plots (right) for the three classifiers.

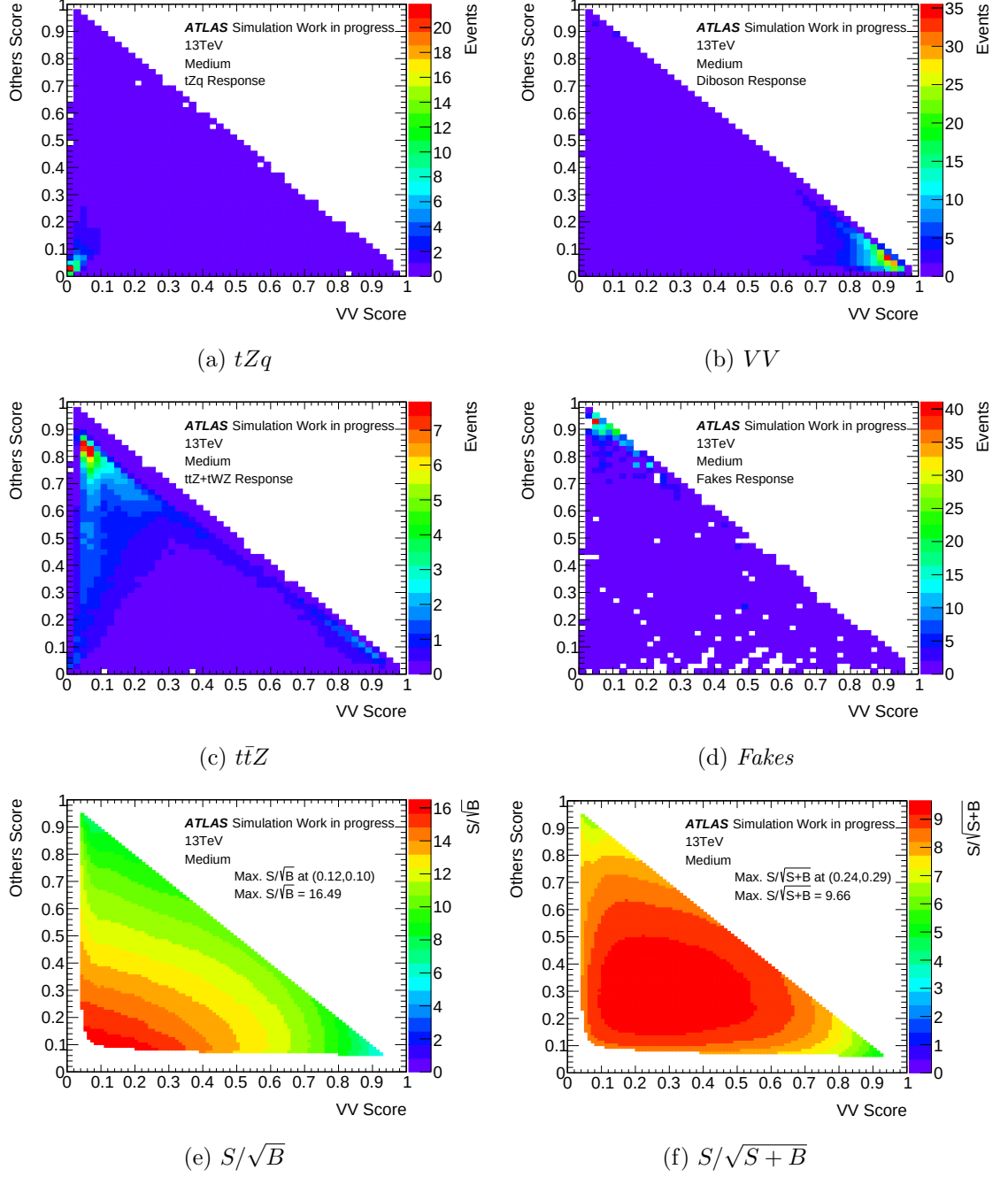


Figure 6.37: 2D response plots in the VV vs $Others$ classifier plane, and signal significance 2D plots in the bottom row.

Standard variables: $t\bar{t}Z$

Following the same steps used for the Lorentz invariant variables, we tested also a $t\bar{t}Z$ MC-3. The purpose of this training is to be able to generate a $t\bar{t}Z$ -enriched region, since the standard variables training for VV allowed for regions definition. The $t\bar{t}Z$ region could not be implemented with the VV MC because $t\bar{t}Z$ belonged to the same target of the Fakes, much greater in event yields, thus resulting in $t\bar{t}Z$ being quite spread in the plane. Therefore, the only way to better separate the $t\bar{t}Z$ background from other background sources is to set it as a target of the Multi Class. The advantage of this is that, since Fakes and Diboson contribution is greater than $t\bar{t}Z$, classifying $t\bar{t}Z$ as the target should avoid the spreading of the remaining sources, as seen for $t\bar{t}Z$ in the previous case, because Diboson and Fakes should be well classified together by the *Others* classifier.

The same variables used in the VV training were used, and the hyperparameter optimisation returned similar values as well, with the only differences being a lower learning rate (0.0001) and the dropout rate removal, as well as the use of only 2 folds for the cross-validation.

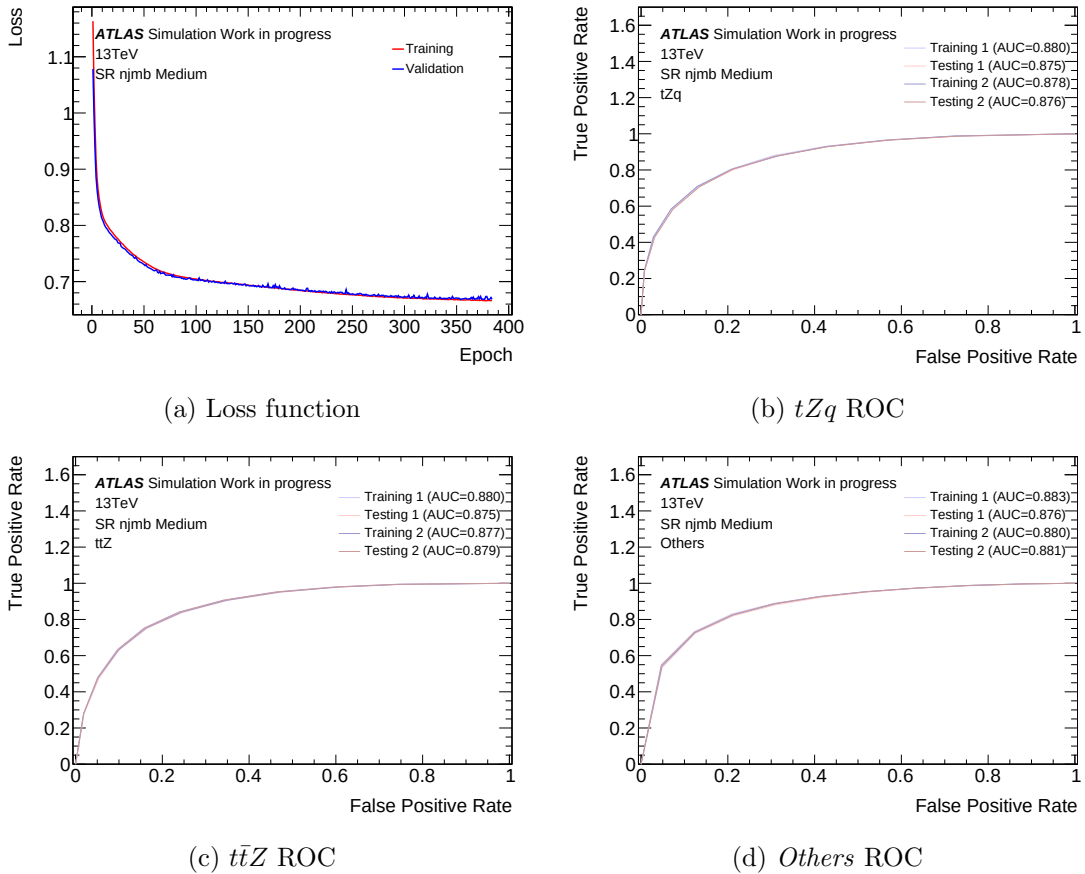


Figure 6.38: Loss function (top right) and ROC curves for the three classifiers

The training performance is improved with respect to the VV training. The loss

function converges at 0.68, similar to that of VV , whereas the AUCs report a significant upgrade, with all of them being around 0.88, compared to the 0.85 AUC of the *Others* classifier for the VV MC-3 NN. Moreover, the confusion matrix diagonal elements are greater especially for the *Others* classifier, since there are more events in this target, and the $t\bar{t}Z$ classifier, whereas they are a bit decreased for tZq , dropping from 0.74 to 0.70.

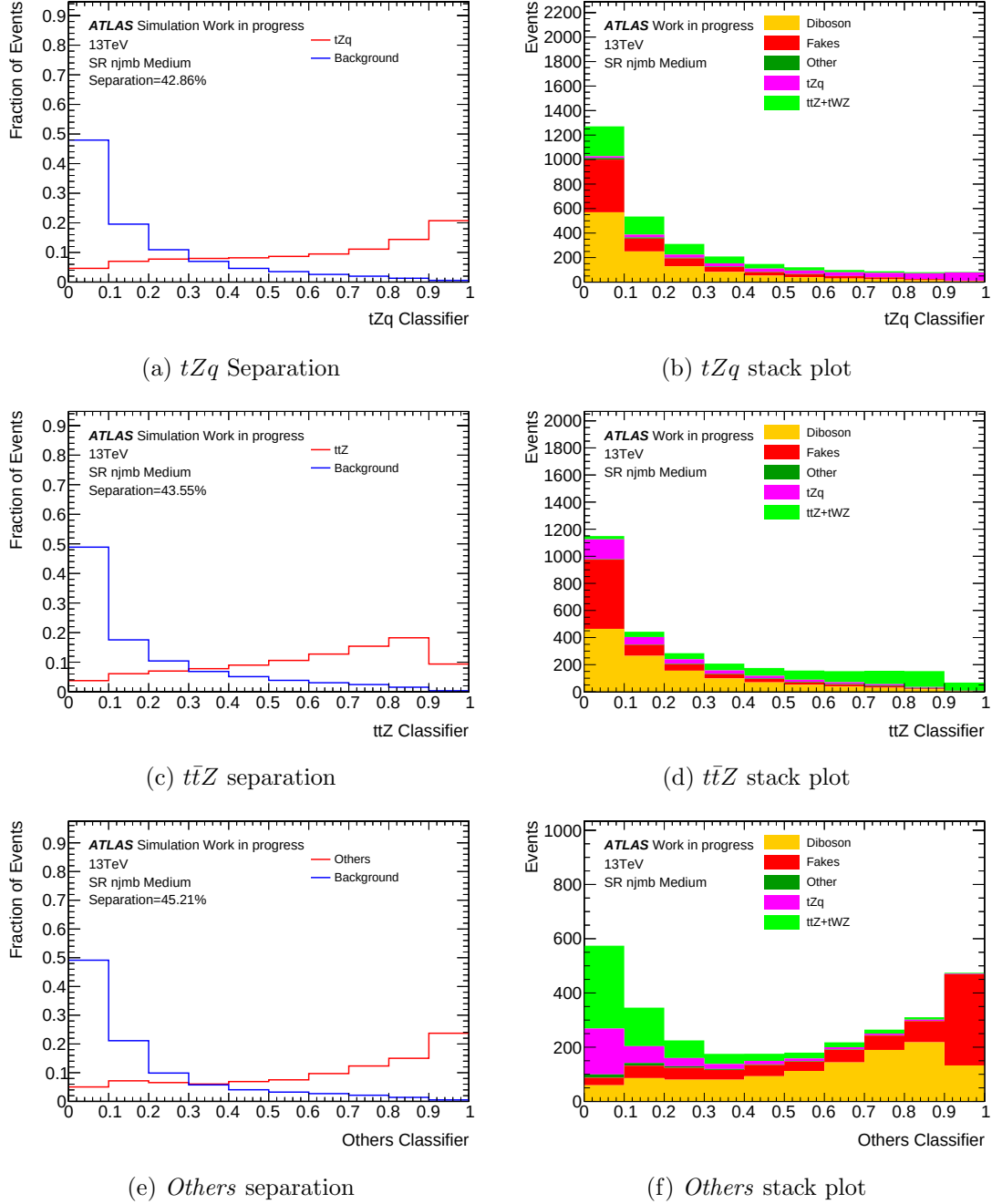


Figure 6.39: Separation curves (left) and stack plots (right) for the three classifiers.

Predictably, the tZq classifier is a bit deteriorated with respect to the VV training,

whereas the remaining two classifiers were significantly improved, as displayed in Figure 6.39.

In detail, the tZq separation value dropped from 44% to 43%. Nevertheless, it is able to classify almost 50% of the backgrounds in the lowest bin and 20% of the signal in the last one, where the signal contribution exceeds the background's by a factor of 4.5. Moreover, all the backgrounds are treated correctly by the classifier, as they all peak in the first bin, an improvement with respect to the VV MC-3. Therefore, in spite of a lower separation and confusion matrix element, this training could result in a better fit than the VV one, even simply for the tZq output.

Similarly, the fit is expected to be better also for the remaining two classifiers. The $t\bar{t}Z$ target has a higher separation than the VV one, 44% instead of 42%, in spite of less statistics given to it. This is due to the fact that Diboson and Fakes are more similar for the selected variables than $t\bar{t}Z$ and Fakes, hence ensuring a Diboson+Fakes classifier (the *Others* classifier) to work better than a Fakes+ $t\bar{t}Z$ one. Of particular interest for the generation of the regions is the fact that the Fakes contribution in the lowest bin of the $t\bar{t}Z$ classifier is almost 70%, with Diboson and tZq following at 40% each. Therefore, we expect to be able to generate a clean region for $t\bar{t}Z$ and for tZq , alongside a Fakes+Diboson-enriched region. This is suggested also by the *Others* classifier, which has a 45% separation, much improved from the 37.5% of the VV training, and it locates 50% of the Fakes and 30% of Diboson in the last two bins.

All the aforesaid considerations are validated by the 2D response plots in Figure 6.40. This training has the best signal localisation, as well as an almost perfect localisation of the Fakes. Diboson and $t\bar{t}Z$ are a bit more spread, but they are still located in the correct corners, hence allowing for clean regions definition. Additionally, this training has also a higher maximum signal significance (9.72, compared to 9.66 of the VV training), thus generating a more enhanced signal region.

The fit which uses this selection is presented in Section 7.2.3

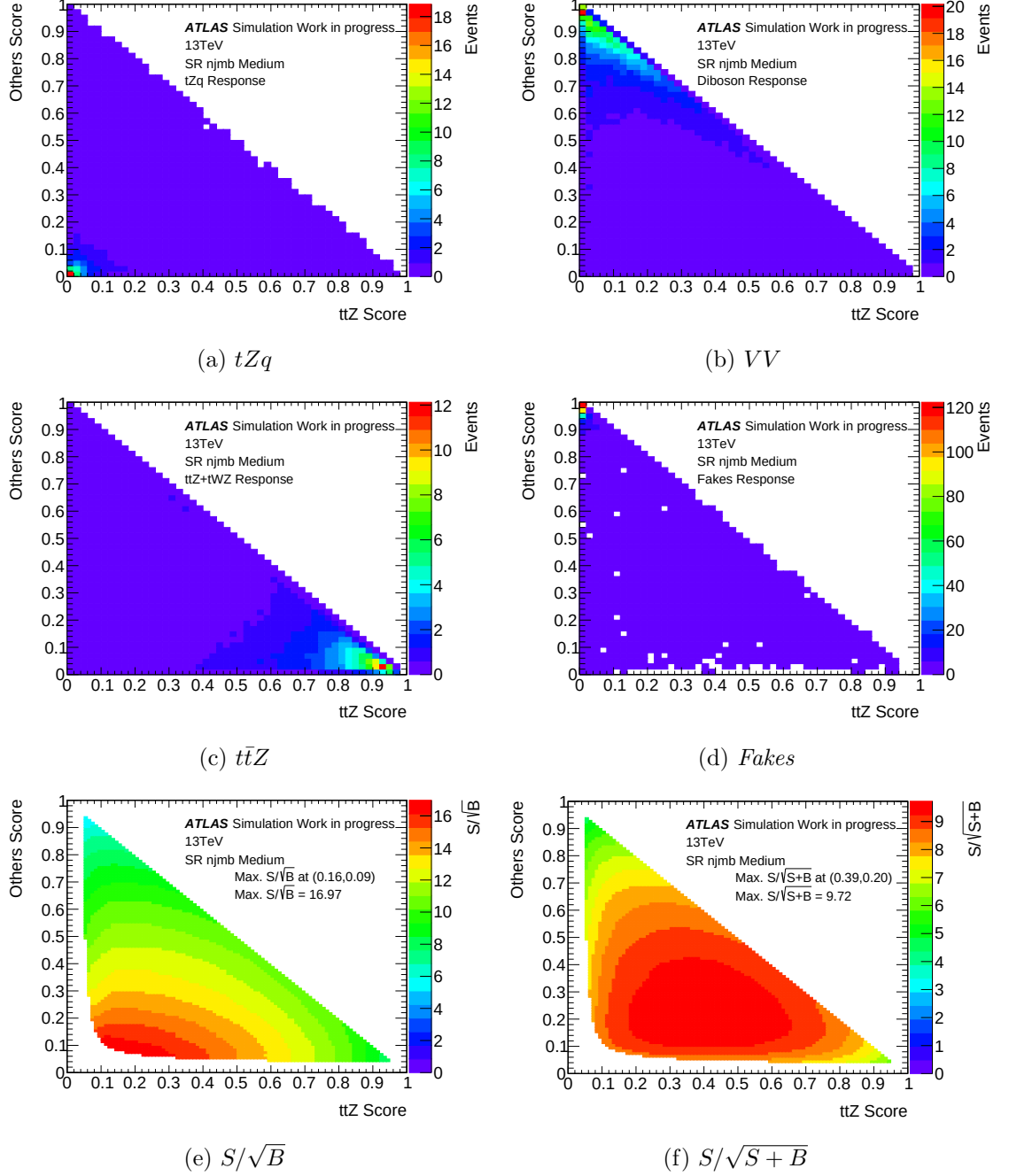


Figure 6.40: 2D response plots in the ttZ vs $Others$ classifier plane, and signal significance 2D plots in the bottom row.

6.4.3 Mixed training

Finally, a different approach to the Multi Class training has been tested. The $t\bar{t}Z$ region dominates mostly the $2b$ -jets region, since it has 2 prompt b -jets, and, on the contrary, Diboson and Fakes events have mostly 1 b -jet. Therefore, in order to improve even more the fit performance, a mixed Multi Class training was implemented: the events with 1 b -jet have been trained with a VV MC-3 (signal(0), VV (1) and *Others* (2)), whereas for events with 2 b -jets the $t\bar{t}Z$ MC-3 NN was used (signal (0), $t\bar{t}Z$ (1) and *Others* (2)). This way, we are exploiting the different contributions as much as possible, at the cost of reducing the statistics for the training. If the training is performed correctly, we expect to be able to create 6 different regions (tZq 1b, VV 1b, *Others* 1b, tZq 2b, $t\bar{t}Z$ 2b and *Others* 2b), where in each one the variable fitted is the NN output of that region.

The event yields for the two classifiers are reported in Table 6.8. It is clear how the $1b$ region will have a better training, since it has 5 times more events than the $2b$. As aforementioned, Diboson and Fakes are mostly located in the $1b$ region, having respectively 94% and 93% of their total events in that region. On the contrary, $t\bar{t}Z$ is almost equally split between the two regions, due to one misidentified b -jet. Nevertheless, in the $2b$ region $t\bar{t}Z$ dominates the event yields, accounting for 52% of the total yields. The signal follows a similar pattern to Diboson and Fakes, though with a smaller difference between the regions: 75% of it is found in the $1b$ region and 25% in the $2b$, with the latter accounting for 16% of the total yields in its region.

	SR $1b$	SR $2b$
tZq	244.7 ± 12.9	81.5 ± 9.5
$VV + b$	229.2 ± 8.0	39.6 ± 1.6
$VV + c$	499.7 ± 17.0	24.6 ± 1.2
$VV + l$	404.6 ± 14.2	7.2 ± 0.4
$t\bar{t}Z$	278.8 ± 17.2	271.0 ± 18.4
$t\bar{t}W$	12.3 ± 0.6	9.8 ± 0.6
tWZ	70.6 ± 9.5	26.5 ± 6.1
$t\bar{t}H$	8.6 ± 0.3	8.9 ± 0.3
Fakes	703.4 ± 41.4	56.0 ± 4.7
Other	0.1 ± 0.0	0.3 ± 0.0
Total	2452.0 ± 95.4	523.2 ± 28.1

Table 6.8: Event yields in the two regions used for the training.

For both trainings the same set of 16 variables was used, which is the same as the Binary training (Section 6.4.1) with the addition of the number of jets. Surprisingly enough, the hyperparameter optimisation returned the same hyperparameters displayed in Table 6.6, with the $1b$ region having same hyperparameters as the RJ-2b region and the $2b$ region with the same ones as the no-RJ region.

I will begin by presenting the results for the $1b$ region, and then the $2b$ region results

will be discussed. The fit which uses this two trainings is presented in Section 7.2.3

1b region

This training's performance was improved with respect to the VV training where the jet multiplicities were not split, because the Diboson relative contribution was increased. The loss function, in spite of some fluctuations in the validations, reaches a convergence at 0.67, similar to what obtained before. The AUCs instead are all improved with respect to Figure 6.35, in particular the tZq AUCs, which are all around 0.89, and the *Others* AUCs, with values of 0.87, both 0.02 more than they were for the other training. Furthermore, the confusion matrix elements are greater for every classifier, 0.75 versus 0.73 for tZq , 0.74 versus 0.73 for VV and finally 0.68 versus 0.67 for the *Others*.

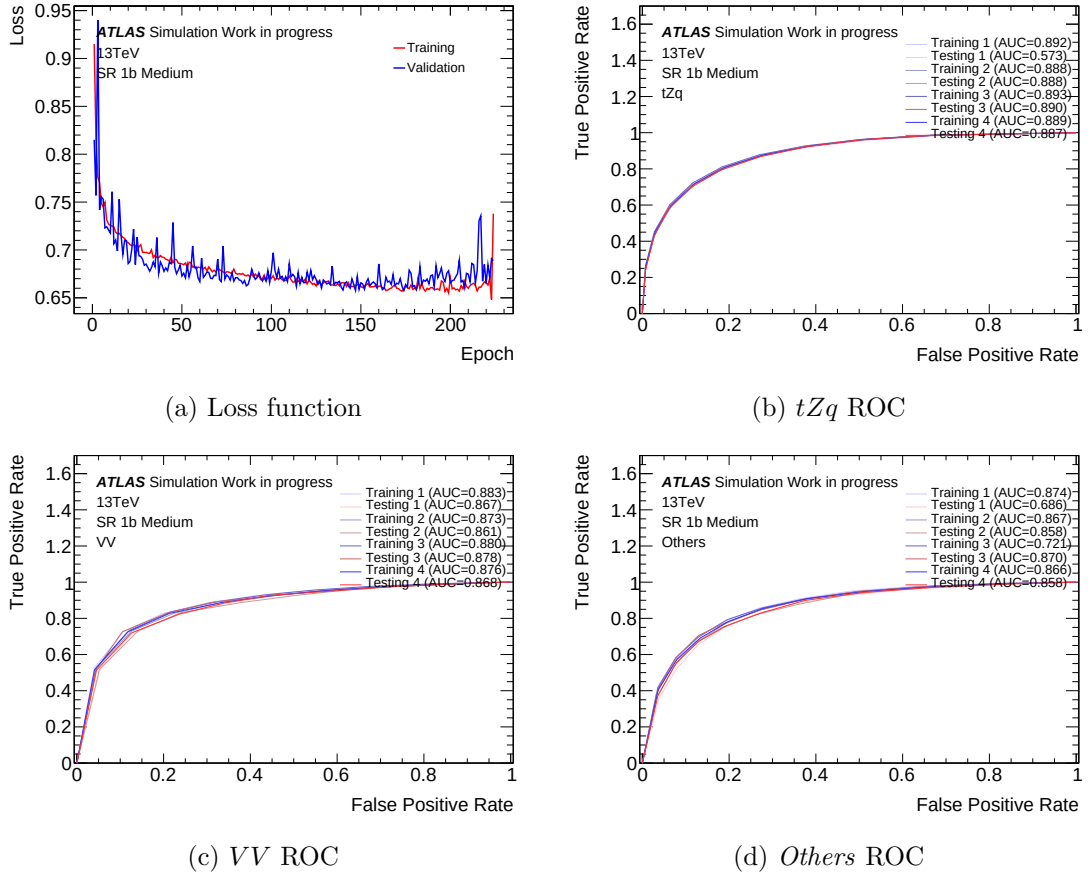


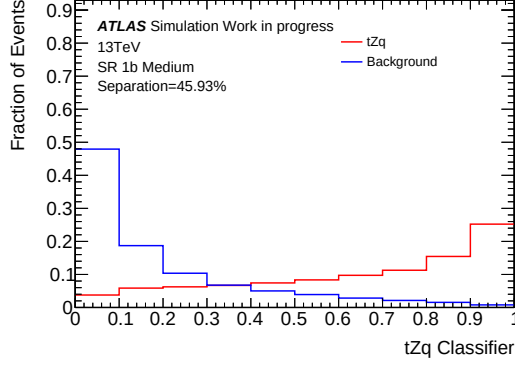
Figure 6.41: Loss function (top right) and ROC curves for the three classifiers

Consequently, all separations (Figure 6.42) are improved with respect to the other VV training. The signal classifier has an almost 46% separation from the backgrounds, the highest obtained for a Multi Class, being able to place almost 50% of the backgrounds in the first bin and less than 1% of them in the last one. The $t\bar{t}Z$ background is the only one not peaking in the first bin, though it peaks in the second one, because of its smaller

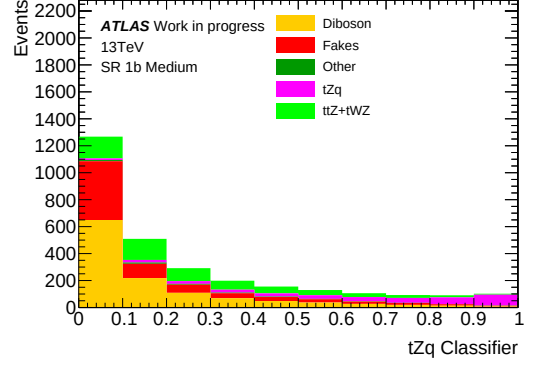
contribution with respect to the other two. Furthermore, 50% of the signal is located in the last two bins.

Analogously, the VV classifier has seen an improvement. The separation rose from 42% to 43%, improving especially in the Diboson contribution in the last bin, increased from 170 to 250 events. A similar situation has been observed for the *Others* classifier, with an increase in the separation (from 37.5 to 39), as well as a greater Fakes contribution in the last bin, from 120 to 180. The $t\bar{t}Z$ distribution, though quite flat throughout the classifier as it was in the previous NN, was improved as well, with the last bin displaying some small contribution in the last bin, contribution which was not present for the NN trained together.

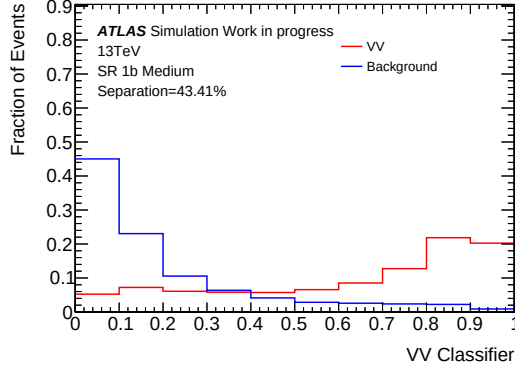
Finally, the 2D response plots (Figure 6.43) tell the same story. The signal is even more localized than it was for the previous training, and the maximum signal significance reached (9.99) is greater than before (9.66). Moreover, Diboson and Fakes are found well localized in their respective corners, as it was the case for the other VV training. The $t\bar{t}Z$ response however is much more spread than before, even if the peak is located at a higher value of the *Others* output. The spreading is due to less $t\bar{t}Z$ events being used in the training. Nevertheless, because less $t\bar{t}Z$ events are found in the $1b$ region, we will still be able to create regions enhanced with different sources, even if the cuts made will have to be looser.



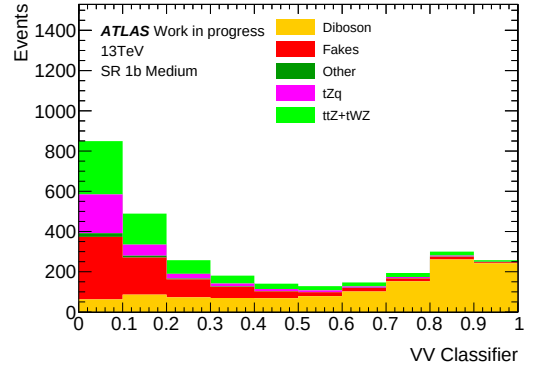
(a) tZq Separation



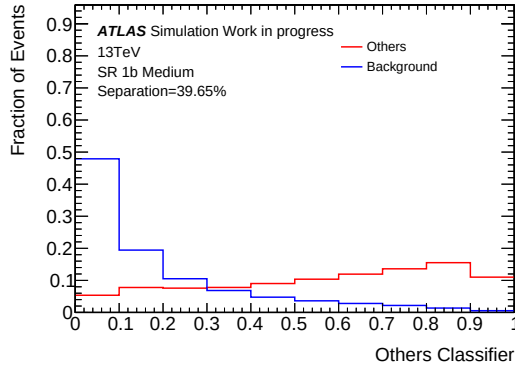
(b) tZq stack plot



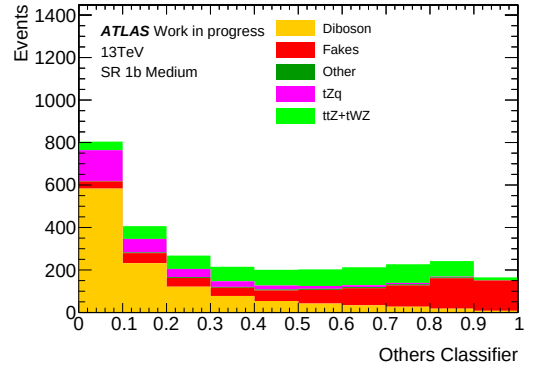
(c) VV separation



(d) VV stack plot



(e) *Others* separation



(f) *Others* stack plot

Figure 6.42: Separation curves (left) and stack plots (right) for the three classifiers.

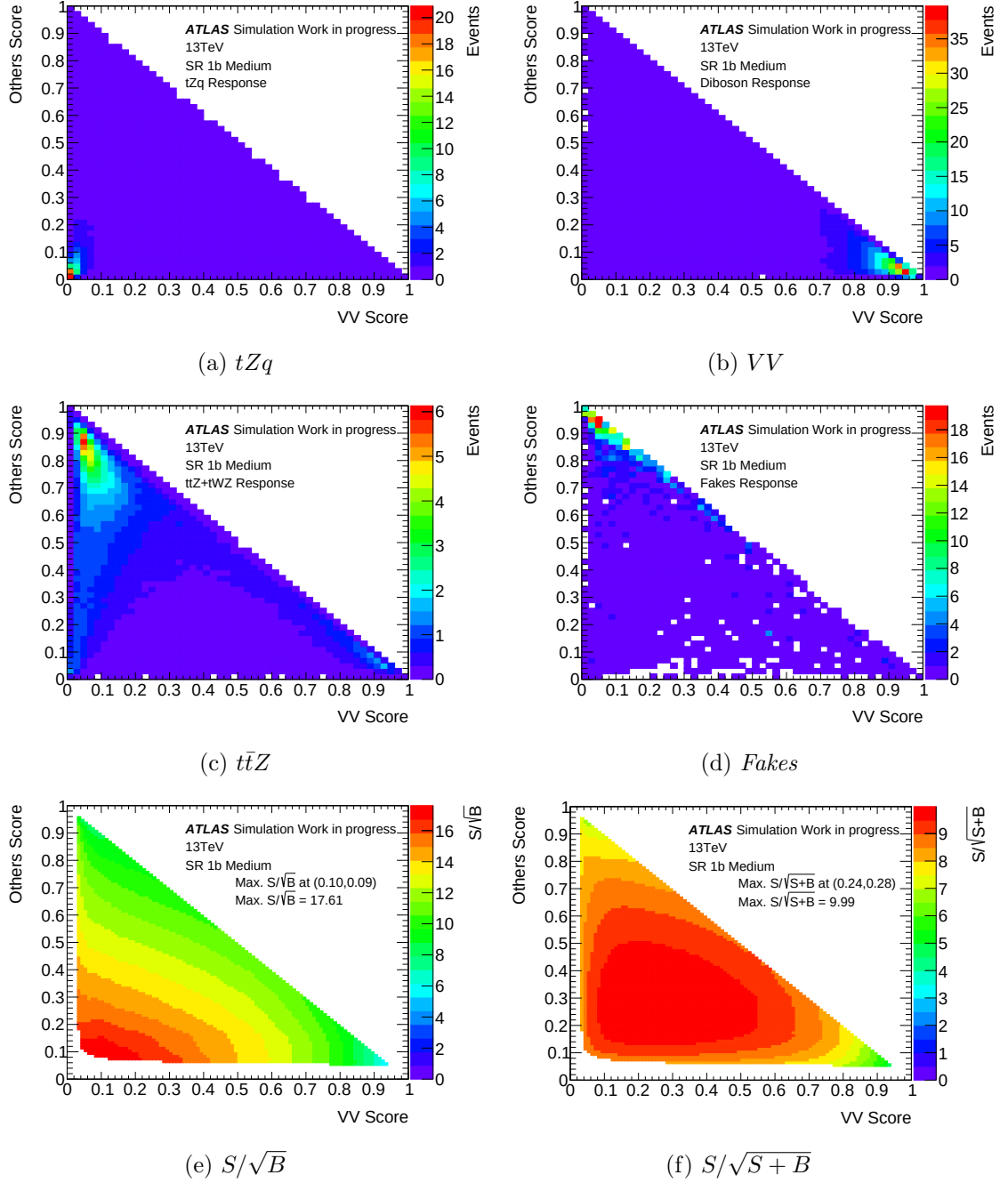


Figure 6.43: 2D response plots in the VV vs $Others$ classifier plane, and signal significance 2D plots in the bottom row.

2b region

At last, I present the Multi Class signal (0), $t\bar{t}Z$ (1) and *Others* (2) in the 2b region, whose yields are reported in Table 6.8. This training is expected to be worse than the MC-3 $t\bar{t}Z$ trained with all regions together, because the yields available are much lower. Nevertheless, because this training will be paired for the fit with the VV training in the 1b region, which turned out to be better than its counterpart trained with all the regions together, we expect the fit to return a better result than the one obtained by using the MC-3 $t\bar{t}Z$ alone.

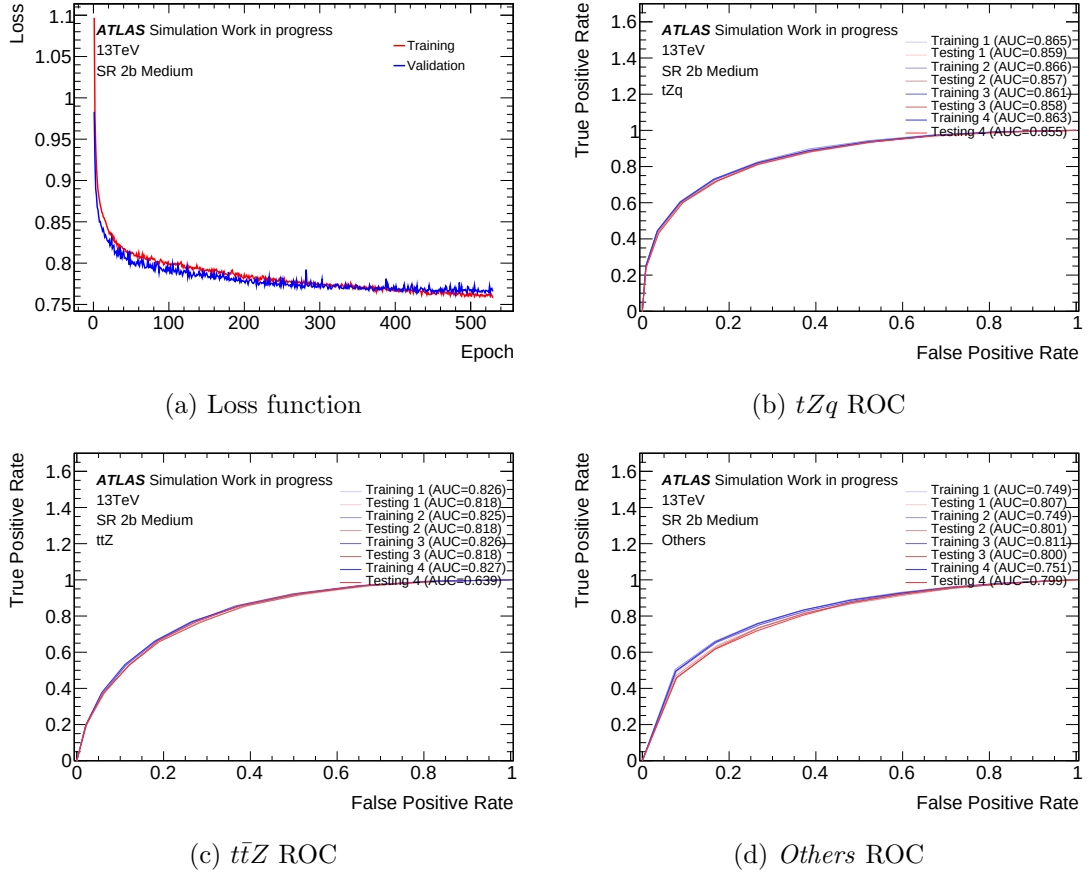


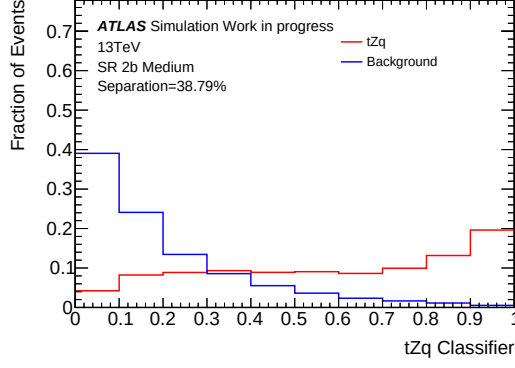
Figure 6.44: Loss function (top right) and ROC curves for the three classifiers

The training results (Figure 6.44) display exactly the expected deterioration. The loss function stops at 0.77, 0.1 more than the other $t\bar{t}Z$ MC-3, and AUCs and confusion matrix elements are all lower as well. In detail, signal AUCs decreased from 0.88 to 0.86, whereas for $t\bar{t}Z$ and *Others* the drop was even more significant, both from 0.88 to 0.81 ($t\bar{t}Z$) and 0.8 (*Others*). Similarly, confusion matrix diagonal elements dropped a bit for tZq (from 0.7 to 0.68) and $t\bar{t}Z$ (from 0.72 to 0.69), whereas for *Others* they fell much more significantly, from 0.73 to 0.61.

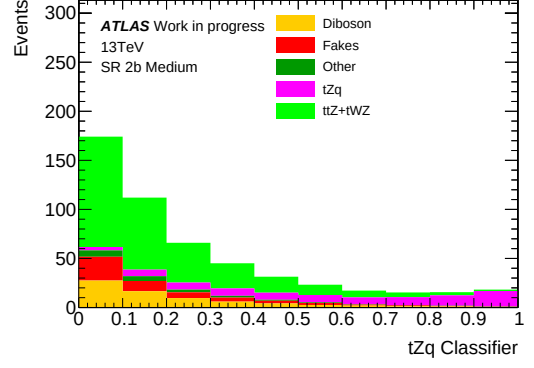
Consequently, separation and stack plots (Figure 6.45) present a much deterioration

with respect to the counterpart trained together. The tZq classifier has a separation of less than 39%, 3% less than the other $t\bar{t}Z$ MC-3. Nevertheless, it is worth noting how all the background distributions peak in the first bin, and in the last bin there is only $t\bar{t}Z$ alongside the signal. However, the $t\bar{t}Z$ and *Others* classifiers display the greatest worsening, with separations lower than 31% for both, with the latter having a 29% separation value, the lowest figure obtained out of all the trainings. Yet, this was expected, because the *Others* yields account for less than 40%, made of different sources as well.

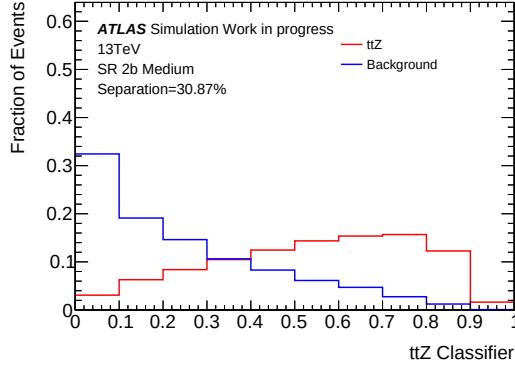
Subsequently, the tZq response is the best one, being located in the bottom left corner, as well as Fakes in the top left one. Diboson however is quite spread all over the plane, but the yields are very low, so that does not worry us too much for the fit. Analogously, the $t\bar{t}Z$ response is stretched out. Similarly to what was said for the $1b$ region, the cuts on this region will be looser as well, in order to try and locate the highest amount of backgrounds in the control regions.



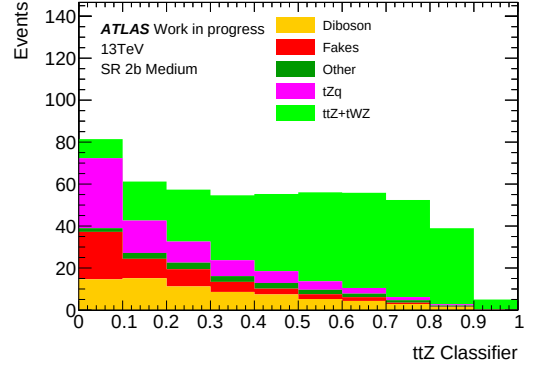
(a) tZq Separation



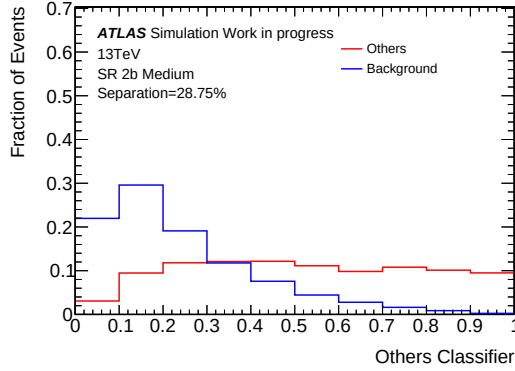
(b) tZq stack plot



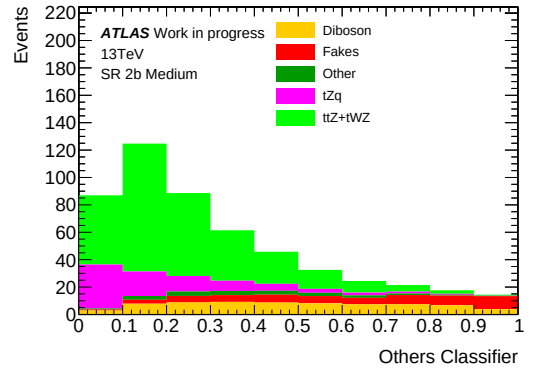
(c) $t\bar{t}Z$ separation



(d) $t\bar{t}Z$ stack plot



(e) *Others* separation



(f) *Others* stack plot

Figure 6.45: Separation curves (left) and stack plots (right) for the three classifiers.

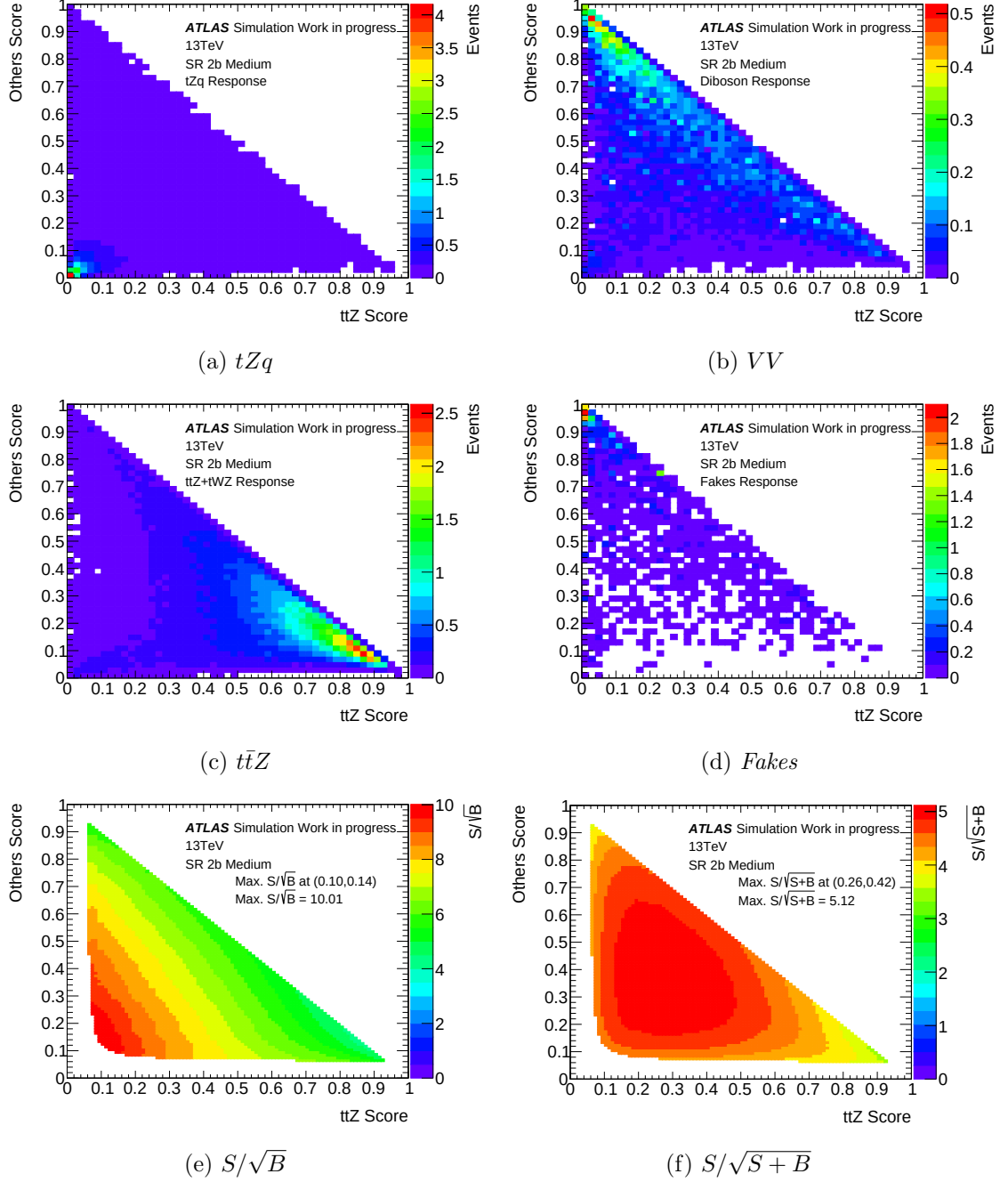


Figure 6.46: 2D response plots in the $t\bar{t}Z$ vs $Others$ classifier plane, and signal significance 2D plots in the bottom row.

6.5 Summary

Here I will present a summary of all the NN trained, specifying the different values for loss function, AUCs, confusion and separation. The trainings not discussed above, either because they performed worse or because they will not be presented in the fit section (Chapter 7), will be reported as well.

In Table 6.9 all tested Binary trainings are summarised, with the last one not being presented in this chapter because for the fit it seemed more convenient to use the Binary training split into three regions. Overall, for the *njmb* region, the optimal selection looks like **Loose**. However, because the **Loose** selection has a lower signal significance than **Medium**, it is the latter which will produce the best fits, as I will present in the next chapter. The best configuration for a Binary training is the **no-RJ** training with the **Medium** selection, as it is the only one who is able to reach a separation over 50%. On the other hand, the **Default** training *njmb* turned out to be the worst, since the statistics available for that training was significantly lower.

Selection	Region	Loss	AUC	Confusion tZq	Confusion bkg	Separation %
Default	<i>njmb</i>	0.52	0.83	-	-	34
Loose	<i>njmb</i>	0.4	0.89	0.82	0.81	47
Medium	<i>njmb</i>	0.43	0.89	0.80	0.81	45
Default	no-RJ	0.46	0.86	0.75	0.80	38
Default	RJ	0.48	0.85	0.77	0.77	38
Medium	noRJ	0.38	0.91	0.84	0.82	51
Medium	RJ-1b	0.42	0.89	0.80	0.80	44
Medium	RJ-2b	0.48	0.85	0.75	0.79	38
Medium	RJ	0.43	0.88	0.80	0.79	44

Table 6.9: Summary of all the Binary trainings performed.

Finally, I will present in Table 6.10 a summary of all Multi Class trainings performed, also the ones which were not discussed in the chapter.

Same as the Binary, the best training for each setup was obtained with the **Loose** selection, whereas the **Default** selection is the one which reported the worst ones, due to its reduced statistics. Nevertheless, the increase in both total signal events and signal significance in the **Medium** selection resulted in better fits with the selection. Additionally, the trainings with the standard variables returned better results than the ones for the Lorentz invariant variables, and this same result will be obtained when doing the fit.

Selection	Name	Region	Target	Loss	AUC	Confusion	Separation %
Default	MC-3 VV	$njmb$	tZq	0.85	0.83	0.70	33
			VV		0.77	0.62	24
			$Others$		0.76	0.55	20
Loose	MC-3: VV	$njmb$	tZq	0.67	0.88	0.77	46
			VV		0.88	0.75	46
			$Others$		0.86	0.66	40
Medium	MC-3: VV (std)	$njmb$	tZq	0.68	0.88	0.74	44
			VV		0.87	0.73	42
			$Others$		0.86	0.68	38
Medium	MC-3: VV (Lor)	$njmb$	tZq	0.68	0.88	0.70	37
			VV		0.86	0.72	39
			$Others$		0.82	0.59	29
Default	MC-3 $t\bar{t}Z$	$njmb$	tZq	0.85	0.84	0.71	36
			$t\bar{t}Z$		0.77	0.60	22
			$Others$		0.76	0.57	21
Loose	MC-3 $t\bar{t}Z$	$njmb$	tZq	0.75	0.85	0.71	45
			$t\bar{t}Z$		0.88	0.72	43
			$Others$		0.88	0.72	46
Medium	MC-3 $t\bar{t}Z$ (std)	$njmb$	tZq	0.66	0.88	0.70	43
			$t\bar{t}Z$		0.88	0.72	44
			$Others$		0.88	0.73	45
Medium	MC-3 $t\bar{t}Z$ (Lor)	$njmb$	tZq	0.76	0.85	0.63	35
			$t\bar{t}Z$		0.83	0.63	32
			$Others$		0.86	0.74	40
Default	MC-4	$njmb$	tZq	1.04	0.83	0.63	34
			VV		0.79	0.61	26.
			$t\bar{t}Z$		0.78	0.52	25
			$Others$		0.83	0.60	35
Loose	MC-4	$njmb$	tZq	0.82	0.89	0.66	45
			$t\bar{t}Z$		0.88	0.67	44
			VV		0.87	0.65	41
			$Fakes$		0.90	0.75	54
Medium	MC-4	$njmb$	tZq	0.82	0.87	0.63	41
			$t\bar{t}Z$		0.87	0.70	44
			VV		0.88	0.66	39
			$Fakes$		0.90	0.72	48
Medium	Mixed VV	$nj1b$	tZq	0.67	0.89	0.75	46
			VV		0.87	0.74	43
			$Others$		0.87	0.69	40
Medium	Mixed $t\bar{t}Z$	$nj2b$	tZq	0.77	0.86	0.68	39
			$t\bar{t}Z$		0.82	0.70	31
			$Others$		0.80	0.61	29

Table 6.10: Summary of all Multi Class trainings.

Chapter 7

Inclusive cross section measurements

In this section I will describe the analysis aimed at measuring the inclusive cross section for the tZq process. All the measurements were performed using the **TRExFitter** framework [91], developed by Tomas Dado, Michele Pinamonti and Alexander Held, which builds statistical models in the HistFactory [92] format.

The fit is made using the maximum Likelihood estimator (MLE) procedure. The Likelihood $\mathcal{L}$ is defined as the product of all probability distribution functions (PDFs, not to be confused with the parton distribution functions, also called PDFs) $f(x_i, \vec{\theta})$, as per Equation (7.0.1), where $\vec{\theta}$ refers to the set parameters and $\vec{x}$ is the set of measurements.

$$\mathcal{L}(\vec{x}, \vec{\theta}) = \prod_{i=1}^N f(x_i, \vec{\theta}) \quad (7.0.1)$$

The MLE are the values $\hat{\theta}_1, \dots, \hat{\theta}_N$ which maximise the Likelihood function, henceforth ensuring that the probability of $\hat{\vec{\theta}}$ to represent the true values is as high as possible. In practical, instead of finding the parameters which maximise the Likelihood, $\hat{\vec{\theta}}$ refer to the parameters which minimise the *negative log Likelihood* (NLL, $-\ln \mathcal{L}$), with the use of the logarithm which allows to rewrite the product of PDFs as a sum of them, as $-\ln \mathcal{L}(\vec{x}, \vec{\theta}) = -\sum_{i=1}^N \ln f(x_i, \vec{\theta})$ ¹².

Due to the excessive size of datasets in high-energy physics analysis, the measured data is grouped into bins. The number of entries in each bin ($\vec{n}$) is distributed according to a Poisson distribution $P = e^{-\nu_i} \nu_i^{n_i} / n_i!$, with mean $\nu_i = \mu S_i + B_i$, which takes into account that in each bin both signal (S_i) and background (B_i) can be present. The parameter μ is the signal strength, which indicates the ratio between observed signal rate S_{obs} and its predicted value S_i . The signal strength is the parameter of interest (POI), which is the parameter for which we are interested on extracting its value with its relative uncertainty,

¹²The NLL is used instead of the log Likelihood simply because for computers it is easier to find the minima of a function instead of finding the maximum.

since it is used to measure the inclusive cross section. Multiple POIs $\vec{\mu}$ can be defined, each referring to the normalisation factors of different processes.

Additional parameters θ_j are called nuisance parameters (NP), and they refer to uncertainties on both experimental procedures and theoretical predictions. Their expected value is usually known beforehand, either by prior experiments or by theoretical models. Therefore, they follow a Gaussian distribution centred around their expected value, with an uncertainty σ . The set of nuisance parameters makes up for the systematics uncertainties.

Consequently, the Likelihood which describes our problem is the one presented in Equation (7.0.2), also denoted *binned profile-Likelihood*. In the formula, P refers to a Poisson distribution with observed data n_i in each bin and expected value $S_i + B_i$ (both extracted from Monte Carlo simulations), G refers to the Gaussian distribution of the NPs $\vec{\theta}$ and $\vec{\mu}$ are the POIs. The product $\prod_j G(\theta_j)$ is the constraint term for the nuisance parameters $\vec{\theta}$, which means that the MLE for this parameter is not free-floating, but it is constrained to follow a Gaussian distribution around its mean value. On the contrary, the POIs are free-floating parameters, and are therefore unconstrained. Additionally, different orthogonal regions $R = 1, \dots, N^R$, either SRs or CRs, can be used to make the most of the available statistics.

$$\mathcal{L}(\vec{n}|\vec{\theta}, \vec{\mu}) = \prod_{i=1}^{N^{bins}} P\left(n_i | S_i(\vec{\theta}, \vec{\mu}) + B_i(\vec{\theta}, \vec{\mu})\right) \times \prod_{j=1}^{N^{NP}} G(\theta_j) \quad (7.0.2)$$

The Likelihood is then a multi-dimensional function, and therefore the fit result is not just the values of the POIs with their respective uncertainties, but it is a set of POIs and NPs which return the minimum value of the NLL.

The uncertainty on the POIs μ is extracted from the fit following Wilks' theorem [90], which states that the profile likelihood ratio $\lambda(\mu)$ (Equation (7.0.3)), which refers to the ratio between the maximised likelihood for a given μ and the absolute maximised likelihood, follows a χ^2 distribution, with $-2 \log \lambda(\mu) = \frac{(\mu - \hat{\mu})^2}{\sigma_\mu^2}$. In addition to the systematics uncertainties, there is also a non negligible statistical uncertainty, because the events are distributed according to a Poisson distribution. Therefore, the total uncertainty is the squared sum of the two separate contributions.

$$\lambda(\mu) = \frac{\mathcal{L}(\mu, \hat{\theta}_\mu)}{\mathcal{L}(\hat{\mu}, \hat{\theta})} \quad (7.0.3)$$

Two different types of fit are implemented: *blind* and *unblinded* fit.

The former is a fit in which real data is not used. Therefore, the fit is made to the Monte Carlo simulated events, resulting in a signal strength measurement of 1. This is due to the fact that the MC simulated data is used as “observed” data, thus making the “observed” data equal to the MC. The purpose of this fit is to measure the uncertainty on the POIs, as well as checking whether the NPs have some pulls or constraint. Additionally, this fit tells which of the NPs are the most important, i.e., the ones which contribute more

to the total uncertainty¹³.

The unblinded fit is, however, a fit made to data. In this fit, the real value of the POIs is measured, because the fit does not force the POIs to be 1. This fit is done only once the analysis strategy has been setup and a definitive configuration for the fit has been reached, in order to avoid any potential bias in the measurement. Additionally, unblinded fits are performed in the control regions, where the signal contribution is negligible, to measure the normalisation factors for different background sources.

The POIs used in this analysis are the normalisation factors (NFs), referring to the ratio between the measured cross section for a process and its expected cross section. Every fit had at least one POI for the signal, called $\mu(tZq)$, alongside additional POIs for Fakes estimation (N_{Fakes}) and $t\bar{t}Z$ ($N_{t\bar{t}Z}$). All fits presented in this chapter are blind, therefore we cannot measure the cross section value but only its uncertainty, as all POIs are set to 1.

On the other hand, the NPs describe the set of systematics. In the following I will present a description of all the systematics used in the fit, alongside a description of how they were treated when needed.

7.1 Systematics description

The systematics uncertainties can be split into *Instrumental* systematics, referring to the object reconstruction and the detector uncertainties, and *Theoretical* systematics, which are related to the modelling of the different processes.

7.1.1 Instrumental uncertainties

158 instrumental nuisance parameters were taken into account in this analysis, and they have been grouped as described in the following:

Luminosity

The luminosity is measured to be $140.1 \pm 1.2 \text{ fb}^{-1}$ [55, 56]. Therefore, to all samples for which a free floating normalisation factor is not defined as a POI, an overall uncertainty of $\pm 0.83\%$ is applied.

Pile-up reweighting

This systematics refer to the uncertainty on the scale factors used by the Monte Carlo to account for differences in pile-up distributions between data and MC. This uncertainty is evaluated using the 3-point variation. Because the nominal scale factor is 1/1.03 (point 1),

¹³The ranking of the NPs is evaluated by performing the fit multiple times, each time by fixing a different NP to $\pm 1\sigma$ (both pre- and post-fit), and evaluating how much the total uncertainty on the POI is affected by the drop of a specific systematics.

the uncertainty is obtained by changing the value to 1/0.99 (point 2) and 1/1.07 (point 3), and then evaluating the effect of the two changes to extract the up and down uncertainty.

Jet energy scale

The jet energy scale (JES) is derived using information provided by test-beam data, collision data and MC simulations. The calibration consists of several steps accounting for detector problems, jet algorithms, jet fragmentation models, enriched data-taking environment from high pile-up conditions and different responses to data and MC. The uncertainty's dependence on η is trivial, whereas it decreases with $p_T(jet)$. A total of 35 Nuisance Parameters were included, divided into pileup (4), modelling (4), detector (2) Jet Vertex Tagger (2, one for j_f), single particle high p_T (1), mixed (3), soft track resolution (3), punchthrough (1), statistical (6), flavour (2), eta intercalibration (6) and finally BJES response (1). As was done for the Pile-up reweighting, all these uncertainties were evaluated with the 3-point variation method.

Jet energy resolution

The jet energy resolution (JER) is measured separately for data and MC using *in situ* techniques. The systematic uncertainty is then defined as the quadratic difference between resolutions for data and MC. When the MC resolution exceeds the data, a smearing in the resolution determined by a Gaussian-distributed factor is applied. 13 total NPs are included.

B-tagging

The efficiency of the DL1r algorithm, used for b -tagging, is calibrated using $t\bar{t}$ and Z +jets data events. The uncertainties are estimated as variations in the tagging efficiencies, thus generating a pseudo-continuous b -tagging calibration. A total of 85 NPs for b -tagging has been considered, with 45 of them being for b -jet identification and 20 each for c and light jets misidentification.

Leptons

A total of 23 NPs were defined for lepton's systematics, 8 for electrons (reconstruction, identification, trigger and isolation, both statistical and systematics, and Egamma scale and resolution) and 15 for muons (2 for isolation, 5 for identification, 2 for trigger, 2 for the sagitta, 2 for track-to-vertex association and one for scale and MS). These NPs account for different scale factors applied to correct the differences between data and simulations in identification, isolation and trigger efficiency. The Egamma NPs checked in simulations using dilepton invariant masses from $Z \rightarrow \ell^+ \ell^-$ and $J/\psi \rightarrow \ell^+ \ell^-$, with scale factors accounting for small variations between data and MC. Once again, their contribution to the total uncertainty is evaluated with the 3-point variation method.

7.1.2 Theoretical uncertainties

A total of 28 NPs were added to account for the theoretical uncertainties, which will be described in the following

PDF

Parton distribution functions are estimated at all scales thanks to the DGLAP equation (Equation (1.5.9)), which requires the knowledge of the PDFs at a given scale Q^2 . Because the cross section measurement depends on the knowledge of the PDFs, as Equation (1.5.10) displays, the uncertainty on the choice of the PDF set and on their derivation is propagated in the cross section. Therefore, having selected the NNPDF3.0NLO PDF set [66], we have reweighted all the events according to each of the PDF uncertainty eigenvectors, as described in [93] in Equation 43.

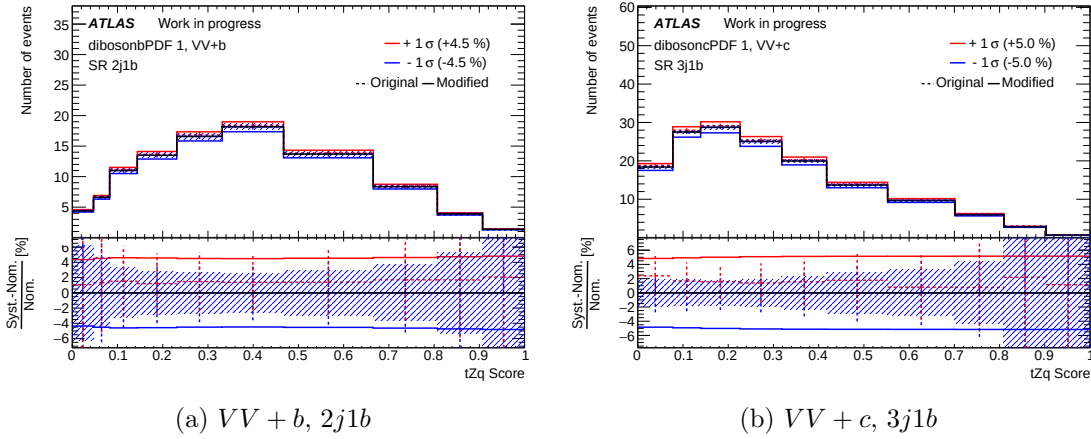


Figure 7.1: Example of PDF systematic on Diboson samples, on the left $VV + b$ in the $2j1b$ region, whereas on the right $VV + c$ in the $3j1b$ region.

PDF uncertainties were included for tZq , $t\bar{t}Z$ and for the three Diboson samples. 101 eigenvectors are defined for each sample, but all of these uncertainties were then merged into 1 NP per sample. However, because the PDF uncertainty on all three Diboson samples had a trivial dependence on the fitted variable in some regions, of which an example can be seen in Figure 7.1, instead of evaluating all the eigenvectors, a fixed value was added based on the jet multiplicity region. For instance, in the $2j1b$ region for Diboson+ b -jet, the fixed value of $\pm 4.7\%$ was added as uncertainty, since, as Figure 7.1(a) displays, the correct uncertainty, evaluated with the eigenvectors, is almost flat and its value is always lower than 4.7 in all bins, being 4.5 on average. Likewise, in the $3j1b$ region for $VV + c$ the uncertainty was set to be $\pm 5\%$. In Figure 7.2 the plots after setting the uncertainty are displayed, and it is clear how they look the same. Therefore, this change does not affect too much the fit and it only helps us saving time for the fit. A similar work had been done in the past for the tWZ PDF uncertainty, which resulted in adding a $\pm 10\%$ uncertainty. This uncertainty has been labelled as “ tWZ normalisation”.

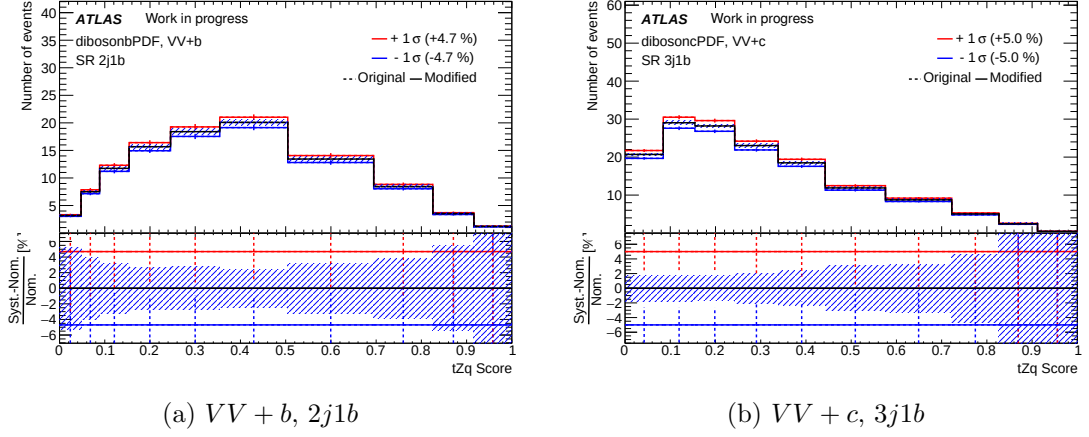


Figure 7.2: Diboson PDF uncertainties after setting them to a fixed value, on the left $VV + b$ in the $2j1b$ region, whereas on the right $VV + c$ in the $3j1b$ region. It is clear how this is not much different than Figure 7.1.

Overall, 6 NPs were added, one for each sample for which the PDF uncertainty was included.

Showering

The showering is the process that occurs after the collision, in which the parton shower is generated. The shower is generated thanks to the splitting of the hard-scattered partons, each having a splitting probability function $P(\alpha(Q^2), z)$ as per Equation (1.5.9), and it is the process which precedes hadronisation. For instance, the signal and the $t\bar{t}Z$ samples are generated using PYTHIA8 for the modelling of the parton shower. Consequently, this choice leads to a modelling uncertainty, which is evaluated by generating a new sample with the same matrix element generator (MADGRAPH5_AMC@NLO) and a different showering algorithm, HERWIG7. The uncertainty is evaluated by using this modified sample for the fit, and seeing how much the normalisation and the shape of the fitted variable differ from the one obtained using the nominal sample. This method of evaluating the uncertainty is called *two-point* variation method, because the uncertainty is obtained by evaluating two different variations of the simulation.

The showering systematics was implemented for tZq , $t\bar{t}Z$ and for the four $t\bar{t}$ samples (split based on the fake lepton origin) with the PYTHIA8 vs HERWIG7 comparison, thus resulting in 6 NPs added.

The showering uncertainty on the tZq sample caused quite a few issues while doing the fits, because we noticed that its impact was higher than expected, as in the previous analysis its contribution to the total uncertainty was negligible. In particular, the problem occurred in fits in which the different regions were split based on jet multiplicity, as Figure 7.3 displays. In the two plots, the same variable has been fitted, which is the output of the Binary NN described in Figure 6.24, but in Figure 7.3(a) the fit uses only

one inclusive SR $njmb$, whereas in Figure 7.3(b) the fit uses 7 different SRs, defined based on jet and b -jet multiplicity ($2j1b$, $3j1b$, $3j2b$, and so on). In the former, the relative uncertainty is greater, around 10%, in the lower bins, where the signal contribution is less, whereas it rapidly decreases to less than 4% in the higher bins, in which the signal contribution dominates. In the latter instead, in spite of having a similar uncertainty in the lower bins, the relative uncertainty in the higher bins reaches also 50%. This has been observed in all the SRs.

A thorough investigation has been carried out as to why this was the case, which will briefly be summarised in the following.

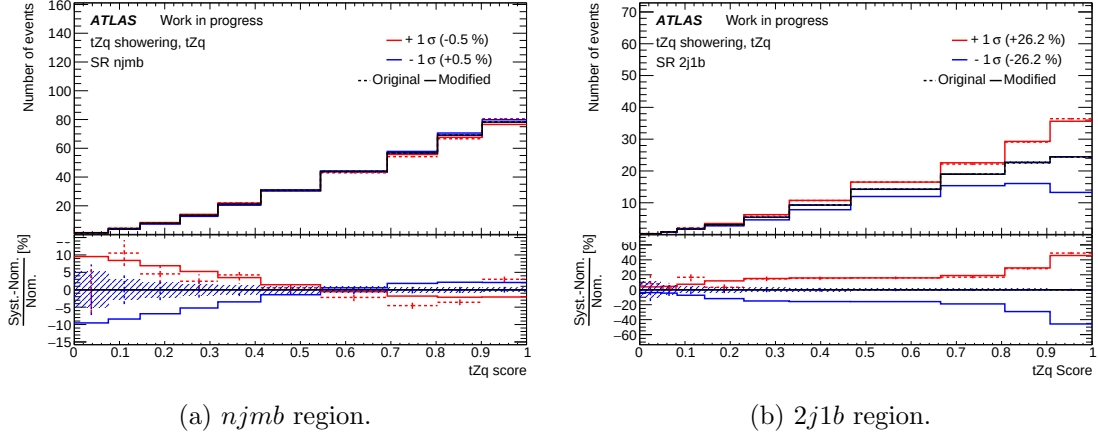


Figure 7.3: Comparison between the showering uncertainty for each bin between the $njmb$ SR (left) and the $2j1b$ SR (in a fit in which the $njmb$ region was split in 7 SRs based on jet and b -jet multiplicity, right), in which it is clear how the uncertainty increases significantly when the regions are split.

We tried to see the systematics dependence on the number of jets and forward jets. We observed the pattern represented in Figure 7.4, where we can see how the uncertainty is high in all but $3j$ jet multiplicity regions, whereas it increases from 5 to 15% as the number of forward jets is increased.

A similar pattern is observed for the $t\bar{t}Z$ showering and for the tZq A14 systematics as well, even though those two uncertainties are overall smaller than they are for the tZq showering. Therefore, this could mean that we are that much sensitive to the tZq showering uncertainty.

μ_R and μ_F

The uncertainty on the renormalization and factorisation scale has been implemented for tZq , $t\bar{t}Z$ and for the 3 Diboson samples, thus resulting in 5 Nuisance Parameters added.

The renormalization scale μ_R refers to the value at which the strong coupling constant $\alpha_s = \alpha_s(\mu_R^2)$ has been evaluated, whereas the factorisation scale μ_F specifies the value at which factorization is applied. These two uncertainties account for the missing higher-

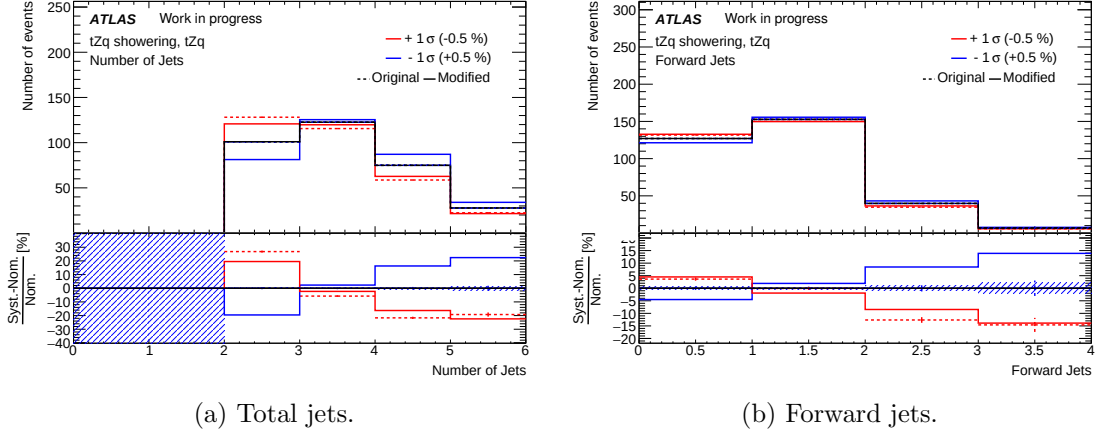


Figure 7.4: tZq showering uncertainty for different values of total jets (left) and forward jets (right).

order terms in the perturbative QCD calculations. μ_R contribution to the cross section comes from α_s dependence on μ_R , as Equation (7.1.1) displays at NLO, where $\alpha_s(\mu_0^2) = \alpha_s(m_Z^2) \simeq 0.12$.

$$\alpha_s(\mu_R^2) = \frac{\alpha_s(\mu_0^2)}{1 + \beta_0 \alpha_s(\mu_0^2) \ln \frac{\mu_R^2}{\mu_0^2}} \quad (7.1.1)$$

Because the signal process is generated in 4-flavour scheme (4FS), the LO has a QCD vertex (for the signal it is the $g \rightarrow b\bar{b}$ in Figures 2.7 and 2.8). Therefore, the NLO cross section is $\sigma = \alpha_s(\mu_R^2)\sigma_0 + \alpha_s^2(\mu_R^2)\sigma_1$, because the QCD vertex at LO generates an α_s dependence which is multiplied to the Born cross section. Consequently, the total cross section dependence on μ_R is much relevant, since α_s influences the lowest order term, even if α_s dependence on μ_R is a higher-order dependence. Therefore, we expect this uncertainty to be important. μ_F instead contributes to the PDF, and thus its contribution in the leading order is less relevant. Consequently, we expect its contribution to be lower than μ_R .

For this uncertainty we tested two different prescriptions given by the ATLAS Physics modelling group. The first one is to test a 5-point variation, in which the μ_R and μ_F parameters are treated separately, and for each a 3-point variation is applied. For example, for μ_R the 3 variations are $\{\mu_R = 0.5, \mu_F = 1\}$ ¹⁴, $\{\mu_R = 1, \mu_F = 1\}$ and $\{\mu_R = 2, \mu_F = 1\}$, where 0.5 and 2 refer to halving or doubling the nominal value. The second setup instead consists of applying only a 3-point variation, in which μ_R and μ_F are varied together, thus resulting in $\{\mu_R = 0.5, \mu_F = 0.5\}$, $\{\mu_R = 1, \mu_F = 1\}$ and $\{\mu_R = 2, \mu_F = 2\}$ for the three points.

Both setups were tested, and in Figure 7.5 the results for tZq are displayed, with the other samples to which this uncertainty was applied showing the same pattern. For tZq μ_F uncertainty is half of μ_R , whereas for the Diboson samples there is a factor of 10 between

¹⁴The value 1 refer to $\mu_R = \mu_F = H_T/6$.

μ_F and μ_R , favouring the latter. The two systematics follow roughly the same shape, and we can see that the combined variation (Figure 7.5(c)) displays the same shape as well, with an uncertainty that covers both separate uncertainties. Moreover, the ranking plot (Figure 7.5(d)) tells us that the contribution from the combined variation to the total uncertainty takes into account the two separate variations. Therefore, only the combined variations were included, thus generating 5 total NPs.

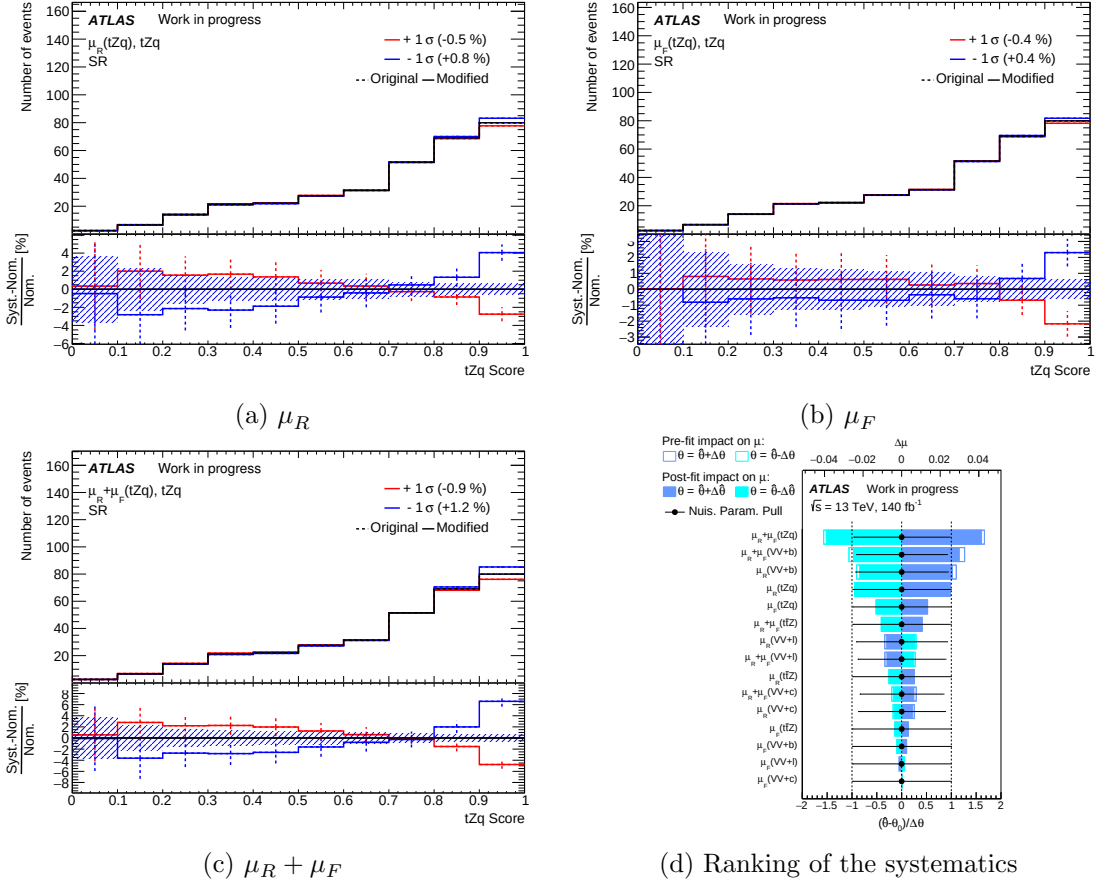


Figure 7.5: Comparison between 5-point variation (top, left for μ_R and right for μ_F) and 3-point variation combined μ_R and μ_F (bottom left). Bottom right plot displays the contribution of the different systematics to the total uncertainty.

A14

The A14 (*ATLAS* 2014, [68]) tune refers to a set of PYTHIA8 tuned parameters used to model initial and final state radiation (ISR and FSR), underlying event and jet structures. The uncertainty due to ISR and FSR is estimated by comparing the nominal sample with two additional samples with same settings as the nominal one, but have employed the Var3c up or down variation of the A14 tune, which corresponds to the variation of the strong coupling constant α_s .

Because this uncertainty is correlated to the modelling of the parton shower, we observed the same dependence from number of jets and forward jets as the tZq showering. This uncertainty was applied on tZq and $t\bar{t}Z$, thus generating 2 additional NPs.

tWZ modelling

A modelling uncertainty on the tWZ background is applied considering the difference between samples generated with the DR1 vs DR2 diagram removal scheme [94], to account for the interference between $t\bar{t}Z$ and tWZ . The DR1 sample is generated removing the amplitude of the doubly resonant process, thus resulting in the matrix element having only the singly resonant term, as also the interference term is removed. The DR2 instead removes only the squared amplitude of the doubly resonant, keeping the interference term intact. With this method, gauge invariance is lost, but the effects due to gauge dependence have been found to be negligible. Overall, this uncertainty contributes for 1 NP.

$t\bar{t}$ modelling

Finally, for $t\bar{t}$ we included the modelling systematics on the hard scattering generator and on the ISR. For the generator, the uncertainty is evaluated through the comparison between the nominal sample, generated using POWHEGBOX+PYTHIA8, and another sample generated using MADGRAPH5_AMC@NLO+PYTHIA8. Analogous to the signal, the uncertainty on the ISR was estimated by the comparison between the nominal sample, in which h_{damp} was set to $1.5m_{top}$, and a sample with $h_{damp} = 3m_{top}$, μ_R and μ_F halved, and applying the Var3c Up variation for the showering.

A total of 8 NPs were added, 2 for each of the *Fakes* CRs.

7.2 Fit: small set of systematics

The systematics are grouped in two different sets: a smaller set was used in the majority of the fits, in order to understand for which configuration it was worth it to run a complete fit with an increased number of systematics. This was done because it takes a lot of time to run the fit with the full set of systematics, sometimes 2-3 days, whereas for the small set the time needed is in the scale of few hours. In the following I will present the fits made using the small set.

The small set includes 25 systematics, grouped in *Theory* (6) and *Instrumental* (19), as shown in the pruning plot in Figure 7.6. The pruning plot is a useful tool to check which systematics are applied separately for each sample and each region. Some systematics are applied only to some specific samples, as it is the case for tZq A14, applied only on tZq . Other systematics instead are applied to all samples, as for instance Luminosity, whose uncertainty affects all samples. However, there are some systematics which are *Dropped* (red boxes in the pruning plot). This means that the systematic contributes too little to the total uncertainty, and therefore can be dropped. Moreover, we can have systematics

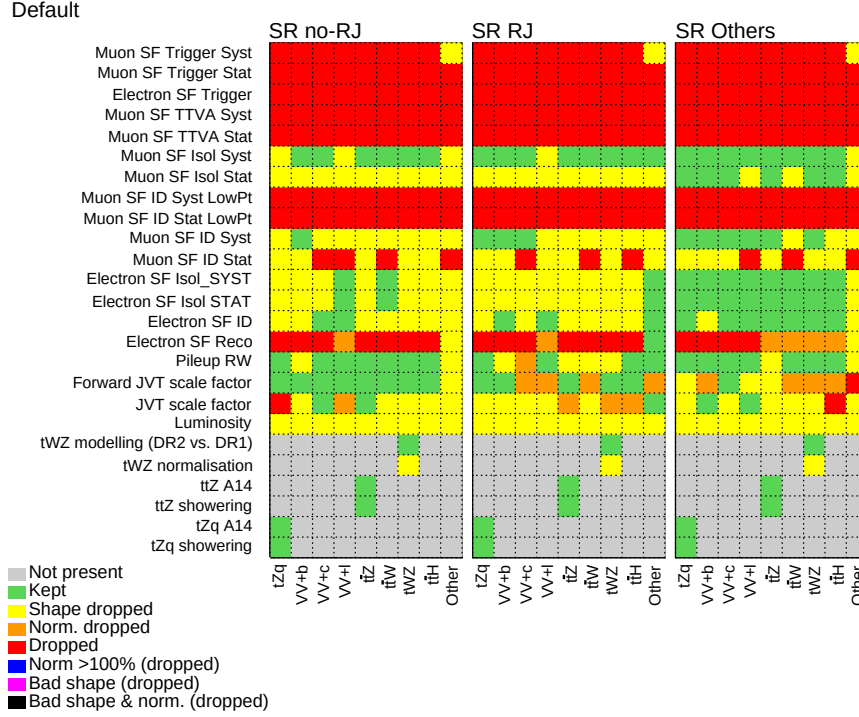


Figure 7.6: Pruning plot displaying the list of systematics belonging to the small set

(yellow boxes) which contribute to the total uncertainty, but only to the normalisation and not to its shape. A case in point is the Luminosity, which contributes with a fixed uncertainty value of 1.2 fb^{-1} . On the contrary, there are systematics (orange boxes) which contribute only to the shape and not to the normalisation, and therefore their contribution to the normalisation is dropped. As Figure 7.6 displays, different systematics can be kept or dropped in different regions for the same samples, except for the Luminosity uncertainty, which is always kept.

The systematics were grouped in tZq modelling (tZq showering and A14), prompt-lepton background modelling and normalisation ($t\bar{t}Z$ showering and A14, tWZ modelling and normalisation), jets reconstruction and calibration, luminosity, pileup modelling, and leptons. These groups were made in order to evaluate the combined impact of these systematics. Furthermore, the impact of the MC statistics, which is the statistical uncertainty in each bin, is evaluated.

In the following, I will be presenting the fits performed using this small set of systematics. All the fits will be Asimov¹⁵, as the analysis has not reached the “Unblind” step, thus resulting in all POIs being 1. I will begin with a description of the fits made with the **Default** and **Loose** selection, respectively in Section 7.2.1 and in Section 7.2.2. Then, I will present the fits made with the **Medium** selection, which will be much more as we immediately noticed that they were looking more promising than the previous selections.

¹⁵ An Asimov dataset is a dataset where the sum of signal and all background expectations is used instead of data.

For all fits, we run an additional fit with the same setup but dropping all the systematics, thus leaving only Poisson terms for signal and backgrounds, each with their statistical Poisson uncertainty $\sqrt{N}$. The lower bound on the uncertainty is evaluated considering all background sources as one, with B events. Then, the relative uncertainty on N events, of which S signal and $B = N - S$ background, is $\sqrt{1/S + 1/B}$. It is clear how this lower bound decreases if more events are found, which is why we tested looser selection to increase the statistics. For the **Default** selection, the lower bound is set at 7.6%, for **Loose** at 6.2% and finally for the **Medium** selection is 5.9%. Therefore, we expect the fits with the **Medium** selection to perform better, since this analysis, much like the old one, is dominated by the statistical uncertainty.

For the best fits, the full set of systematics was also used.

Furthermore, it is important to specify that the luminosity value and uncertainty changed throughout the analysis. ATLAS' integrated luminosity had been measured to be $\int L(t)dt = 139 \pm 2.4(\pm 1.7\%) \text{ fb}^{-1}$, and this is the value that we used in the beginning of the analysis. However, on the 24th of January 2023, ATLAS delivered the most precise luminosity measurement [55, 56], which not only reduced the uncertainty, but it also changed the nominal value, which is now $\int L(t)dt = 140.1 \pm 1.2(\pm 0.83\%) \text{ fb}^{-1}$. Therefore, after the publication, we started using this new value for luminosity. All fits with the **Default** and **Loose** selection have been performed before the new measurement, and therefore their yields are scaled to a luminosity of 139 fb^{-1} , whereas all fits with the **Medium** selection have been performed with the new luminosity measurement implemented. Consequently, the luminosity label has been added in all the plots, in order to help on discriminating the two different luminosity uncertainties used.

7.2.1 Default selection

In this section the fits with the **Default** selection will be presented. The yields for this selection are presented in Table 4.6, whereas the MVA trainings which will be used in the following fits are described in Section 6.2.

These fits all use the small set of systematics presented in Figure 7.6, and the luminosity value to which the cross section has been scaled to is $139 \pm 2.4 \text{ fb}^{-1}$.

For this fits, the Diboson sample was split based on the jet flavour, thus generating three different samples: $VV + b$, $VV + c$ and $VV + l$. Moreover, the $t\bar{t}Z$ sample was not merged with tWZ , and *Others* sample of the training was split between $t\bar{t}H$, $t\bar{t}W$ and *Others*, made up only of 3 and 4 top production. Furthermore, the **Autobin** function from **TRExFitter** was used in all fits, in order to have bins which maximise the separation between signal and background, focusing the majority of the backgrounds on the left and the majority of signal on the right. This has proved to bring better results on the fit, as the uncertainty using this function was lower than the one obtained using fixed bins.

Binary

First of all, I will begin with a description of the simplest fit, which is the one using the **Binary** NN output. This setup is the easiest because only one Signal Region is defined, in which the variable fitted is the output of the NN, whose training is presented in Section 6.2.1.

Since this is the first fit I am presenting, I will show all the plots, with an explanation on which informations can be extracted, whereas for the following fits I will present the same plots only when needed.

As aforementioned, this fit has 1 SR with 1 POI, the signal strength $\mu(tZq)$, evaluated as σ/σ^{th} , and 25 NPs. As the fit is Asimov, I will present only the post-fit plot of the signal region, since the effect of the fit is simply to reduce the total uncertainty in the distribution.

The SR plot is presented in Figure 7.7. This plot displays the stack plot of the variable to be fitted, in this case the Binary NN output, labelled as tZq score. 10 bins were used, with the implementation of the **Autobin** function, which explains why the bins are not equally spaced. The blue striped lines represent the post-Fit uncertainty, taking into account all the systematics, in each bin, whereas the χ^2 and the ratio plot are not filled since the fit is Asimov. As expected, we have the signal distribution peaking in the last bin, whereas the backgrounds contribute more in the first bins. Because the separation value was quite low, around 38%, signal and backgrounds are not too much separated, and the plot reflects that. The effect of the fit on the plot is imply to reduce the uncertainty, as displayed in the comparison between the pre-fit (Figure 7.7(a)) and the post-fit (Figure 7.7(b)) plots.

The total uncertainty in the fit is presented in Figure 7.8, in which we can see the comparison between the total uncertainty (Figure 7.8(a)) and the stat-only uncertainty (Figure 7.8(b)). The MLE for the POI is $\mu(tZq) = 1.00^{+0.17}_{-0.15} = 1.00 \pm 0.12(\text{stat})^{+0.11}_{-0.10}(\text{syst})$, thus confirming that the uncertainty on the cross section measurement is dominated by the statistical component. Among the systematics, the leptons uncertainties are the ones contributing the most at 7%, followed by the prompt-lepton background normalisation at 5.3%, due mostly to the $t\bar{t}Z$ showering, and luminosity at 3.6%. The impact of the signal modelling is less than 1.5%, lower than the MC statistics'.

Additional useful informations on the fit can be extracted by looking at the ranking plot (Figure 7.9(a)) and the pull plot (Figure 7.9(b)). The ranking plot is used to evaluate the contribution to the total uncertainty by each systematics. The evaluation works as follow: for each systematics, two fits are performed, setting the value of that particular NP to $\hat{\theta} \pm \Delta\hat{\theta}$, with Δ equalling 1σ . Once the fit is finished, the uncertainty on the POI is evaluated for each case, both for the pre-fit and the post-fit. After this, the effect each systematics has on the total uncertainty is evaluated by looking how much the uncertainty on μ changes in the two scenarios. The post-fit impact is represented in the plot with the two coloured boxes, the lighter for fixing the NP to $\hat{\theta} - \Delta\hat{\theta}$ and the darker for $\hat{\theta} + \Delta\hat{\theta}$, whereas the pre-fits are represented with the white boxes. Both the pre- and

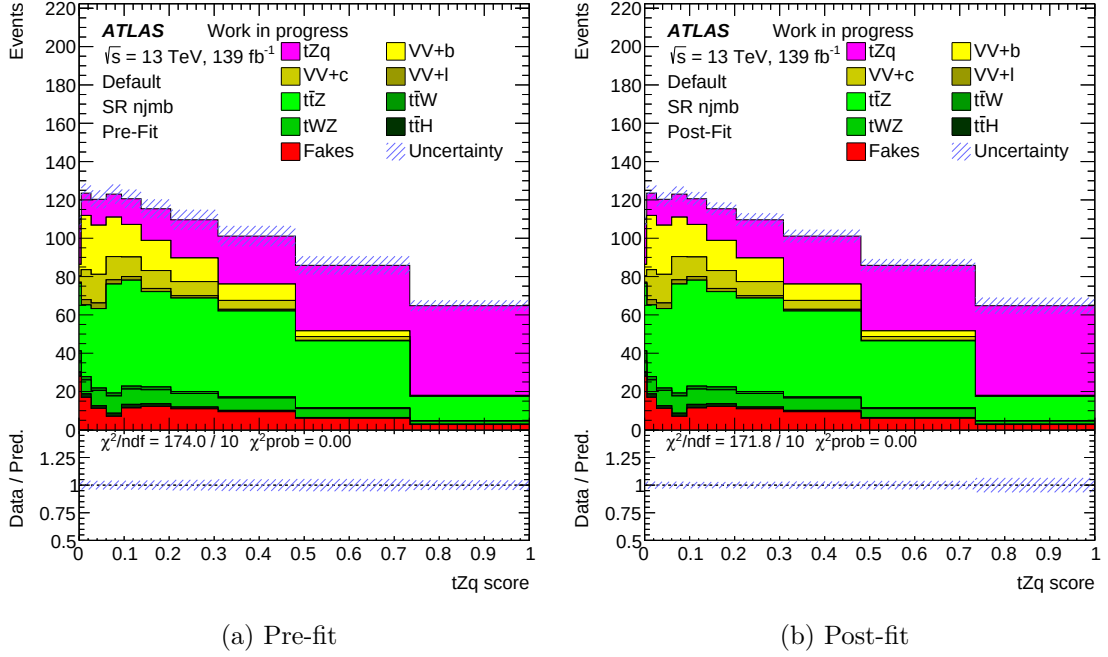
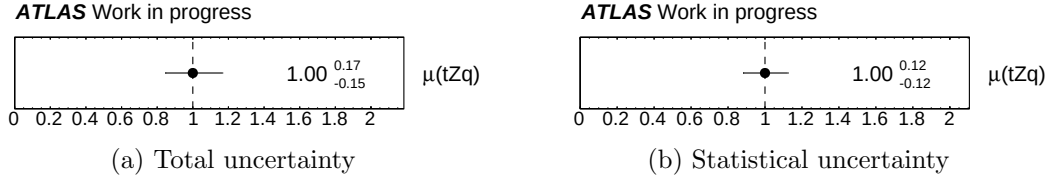


Figure 7.7: Pre- (left) and post- (right)-fit SR plot displaying the NN output distribution.


 Figure 7.8: POI total uncertainty (left) and stat-only uncertainty (right) for the Binary fit with the `Default` selection.

post-fit contributions are evaluated using the top axis, labelled as $\Delta\mu$. The bottom axis instead is used to evaluate whether the systematics are constrained, same as the pull plot (Figure 7.9(b)). The dark circle specifies the difference between the MLE for a NP and its nominal value. For all Asimov fit, the value is always 0, unless the systematic is a γ , which refers to the statistical uncertainty in each bin, for which its nominal value is 1. The dark horizontal line tells how much the uncertainty on the NP is greater than 1σ . If the dark line reaches the value 1, or if it differs slightly, then the NP is not constrained. On the contrary, if the dark line does not reach 1, it means that there are some constraints.

For this fit, we can see that no significant pulls are present, and only the $t\bar{t}Z$ showering uncertainty displays a small constraint. The ranking on the other hand tells that the same uncertainty is the leading one, with a relative contribution to the total uncertainty of 5%. Luminosity sits at the second place, with an impact of 4%, and all the lepton uncertainties follow immediately after, accounting for a total of 7% uncertainty. As thoroughly discussed in Section 7.1.2, we expected the tZq showering uncertainty contribution to be negligible, because all the events with different jet multiplicities are kept together, and we observed

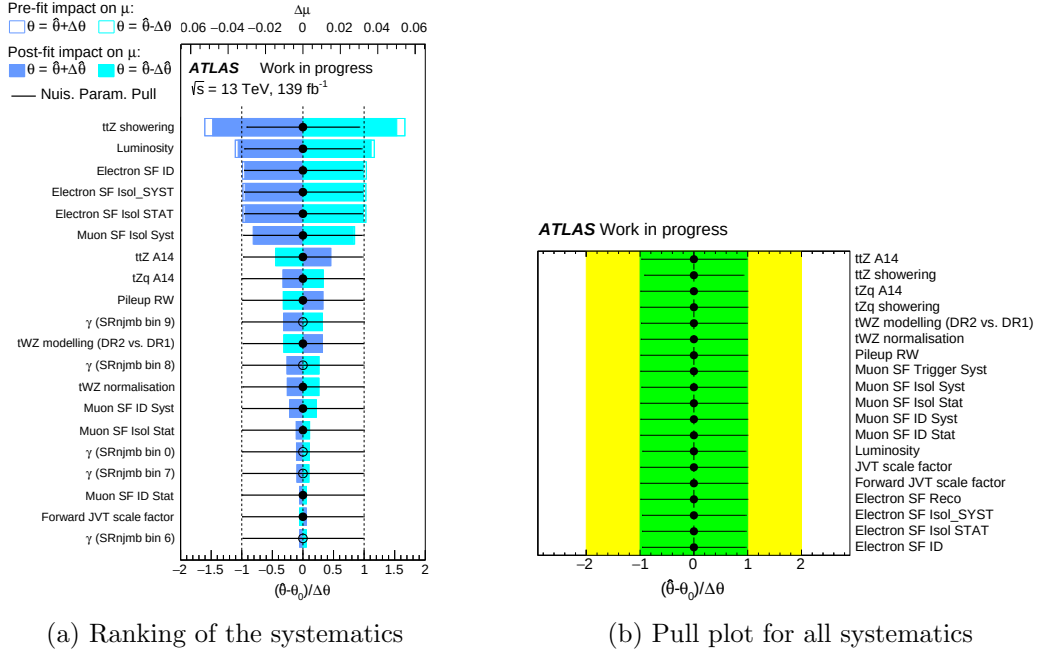


Figure 7.9: Ranking (left) and pull plot (right) of all systematics for the Binary fit with the **Default** selection.

this because the tZq showering uncertainty is not among the top 20 ranked systematics, with an impact of 0.1%.

Finally, it is interesting to have a look at the correlation matrix, presented in Figure 7.10, where only systematics with at least one correlation above 5% are displayed. It is immediately apparent how, as expected, the highest ranked systematics are the ones with the highest correlation with the POI. On the other hand, no significant correlations are found between the NPs.

To summarise this fit, which will be use as a baseline for comparison with the other fits, we have 1 SR with 10 bins, 1 POI and 25 NPs, the total uncertainty on the POI is $+17\% -15\%$ and no significant constraints are found. This uncertainty is higher than what had been obtained during the previous analysis ($\pm 14\%$), therefore we tried different setups, which will be presented below, in order to reduce it.

ATLAS Work in progress

Electron SF ID	100.0	-6.5	-6.5	-7.2	-5.0	1.6	-3.0	3.7	0.2	0.7	4.8	-20.0
Electron SF Isol STAT	-6.5	100.0	-6.4	-7.1	-4.9	1.5	-2.9	3.6	0.2	0.2	4.8	-19.9
Electron SF Isol_SYST	-6.5	-6.4	100.0	-7.1	-4.9	1.5	-2.9	3.6	0.2	0.2	4.8	-19.9
Luminosity	-7.2	-7.1	-7.1	100.0	-5.4	1.7	-3.2	4.0	0.2	0.6	5.2	-22.4
Muon SF Isol Syst	-5.0	-4.9	-4.9	-5.4	100.0	1.2	-2.3	2.8	0.2	0.5	3.6	-16.6
Pileup RW	1.6	1.5	1.5	1.7	1.2	100.0	0.7	-0.8	-0.1	-0.5	-1.1	6.6
tWZ normalisation	-3.0	-2.9	-2.9	-3.2	-2.3	0.7	100.0	1.7	0.1	-0.1	2.2	-5.3
tWZ modelling (DR2 vs. DR1)	3.7	3.6	3.6	4.0	2.8	-0.8	1.7	100.0	-0.1	0.4	-2.7	6.4
tZq A14	0.2	0.2	0.2	0.2	0.2	-0.1	0.1	-0.1	100.0	-0.2	-0.1	-6.7
ttZ showering	0.7	0.2	0.2	0.6	0.5	-0.5	-0.1	0.4	-0.2	100.0	-0.1	-31.0
ttZ A14	4.8	4.8	4.8	5.2	3.6	-1.1	2.2	-2.7	-0.1	-0.1	100.0	9.1
$\mu(tZq)$	-20.0	-19.9	-19.9	-22.4	-16.6	6.6	-5.3	6.4	-6.7	-31.0	9.1	100.0
	Electron SF ID	Electron SF Isol STAT	Electron SF Isol_SYST	Luminosity	Muon SF Isol Syst	Pileup RW	tWZ normalisation	tWZ modelling (DR2 vs. DR1)	tZq A14	ttZ showering	ttZ A14	$\mu(tZq)$

Figure 7.10: Correlation matrix between all systematics and the POI, displaying only systematics with at least one correlation above 5%.

Binary splitting regions

With the idea of reducing the total uncertainty, we decided to try a more complex setup. For this fit, 3 orthogonal SRs were defined, based on jet multiplicity, as Table 7.1 displays. The first region, labelled as **no-RJ**, includes events with either 2 jets, of which 1 *b*-jet, or 3 jets, of which 2 *b*-jets. These events are the events which do not have a radiation jet, because they only have one forward jet and *b*-jets. The RJ region instead includes events which have a radiation jet, so the jet regions *3j1b* and *4j2b*. Finally, the *Others* region includes events either with no forward jets (*2j2b*) or with more radiation jets (*4j1b*). The *2j2b* region was added in order to increase the statistics in the *Others* region, in which the fit was not made to the NN output because the training was made only in the other two regions, as presented in Section 6.2.1. The variable $p_T(Z)$ was chosen as it provides a decent separation between $t\bar{t}Z$, which is the background that dominates the region, and the remaining sources.

Post-fit yields and the summary plot with all the regions, which is just a way to visualize the post-fit yields, are presented in Figure 7.11. As aforementioned, the $t\bar{t}Z$ background dominates the *Others* region, accounting for more than 50% of all yields in

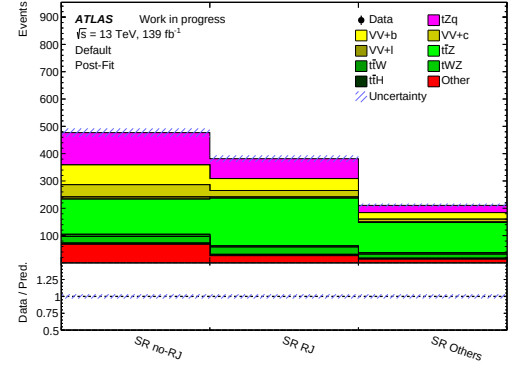
	SR no-RJ	SR RJ	SR Others
Jet regions	2j1b, 3j2b	3j1b, 4j2b	2j2b, 4j1b
Number of bins	10	10	10
Variable fitted	O_{tZq}^{no-RJ}	O_{tZq}^{RJ}	$p_T(Z)$

Table 7.1: SRs definition for the fit using the Binary NN outputs trained splitting the regions.

the region, whereas the **no-RJ** region has an almost equal contribution of signal, $t\bar{t}Z$ and Diboson, alongside the highest contribution from the *Others*, which is mostly *Fakes*. Finally, the RJ region has more than twice as much $t\bar{t}Z$ than both tZq and Diboson, with the other background sources contribute little to nothing.

	no-RJ	RJ	Others
tZq	118.1 ± 14.7	72.8 ± 11.6	26.5 ± 4.5
$VV + b$	72.6 ± 2.3	43.7 ± 1.4	24.2 ± 0.8
$VV + c$	44.8 ± 1.4	23.9 ± 0.7	10.2 ± 0.3
$VV + l$	8.0 ± 0.3	4.3 ± 0.1	1.9 ± 0.1
$t\bar{t}Z$	128.9 ± 10.8	174.5 ± 11.1	110.6 ± 6.6
$t\bar{t}W$	7.8 ± 0.2	4.5 ± 0.1	5.4 ± 0.2
tWZ	24.3 ± 8.0	26.7 ± 9.4	14.8 ± 5.5
$t\bar{t}H$	4.4 ± 0.1	4.8 ± 0.1	3.4 ± 0.1
Other	68.2 ± 2.1	26.5 ± 0.8	13.7 ± 0.5
Total	477.0 ± 15.7	381.6 ± 12.4	210.6 ± 6.7

(a) Post-fit SR yields



(b) Summary plot with all regions

Figure 7.11: Post-fit SR yields (left) and summary plot with all regions (right) for the fit with the **Default** selection using the Binary NN trained splitting regions

Because the NNs were trained separately in the same regions used for the fit, we expect this fit to perform better, as we are able to provide a better separation in each region, alongside an increased number of information given to the fit. The post-fit plots in Figure 7.12 represents exactly this: in the two regions in which the NN was trained, the signal distribution peaks in the last bin, whereas both $t\bar{t}Z$ and Diboson follow the opposite pattern. Only the *Fakes* are not well separated from the signal, as their statistics in this region was too little to perform a proper training.

The additional advantage that comes from splitting the regions is that we are able to create a region enriched with $t\bar{t}Z$ (the *Others* region). Therefore, we might be able to reduce the impact of the $t\bar{t}Z$ showering uncertainty, because the fit should be able to better treat the $t\bar{t}Z$ systematics. On the other hand, we expect the impact from the tZq showering to increase, because we are splitting the regions based on jet multiplicity, and, as discussed in Section 7.1.2, this leads a significant impact of the tZq showering uncertainty.

The total and statistical-only uncertainties are presented in Figure 7.13. The MLE

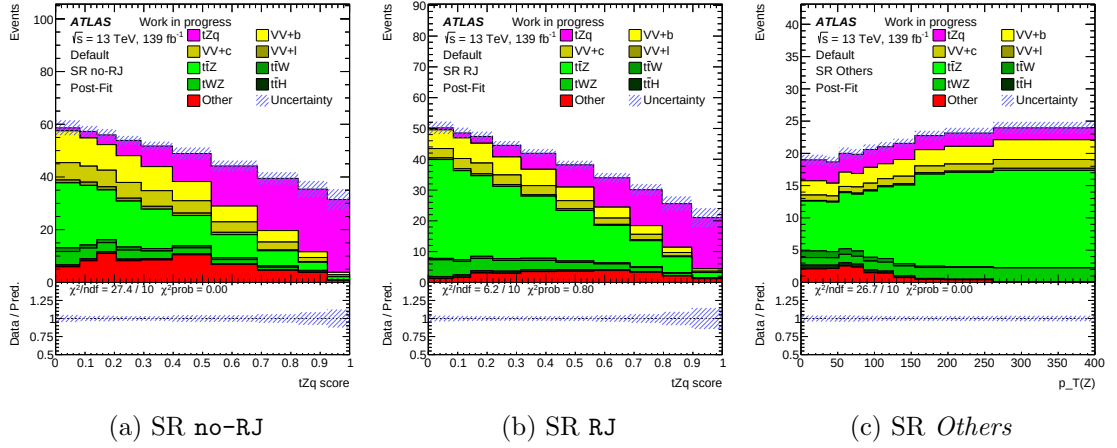


Figure 7.12: Post-fit SR plots for the fit with the **Default** selection using the Binary NN trained splitting the regions.

for the POI is $\mu(tZq) = 1.00 \pm 0.13 = 1.00_{-0.10}^{+0.11}(\text{stat})_{-0.08}^{+0.09}(\text{syst})$. Once again, we are dominated by statistics, even if the statistical uncertainty was reduced with respect to the fit keeping all regions together (Figure 7.8(b)). Systematics uncertainties were reduced as well, reaching a total of 8%, of which the highest contributions come from prompt lepton modelling (3.9%, dominated by $t\bar{t}Z$ showering), lepton systematics (3.8%) and signal modelling (3.3%). Luminosity's impact was reduced with respect to the previous fit, at 2%, whereas MC statistics contribution was unchanged, at 1.4%.

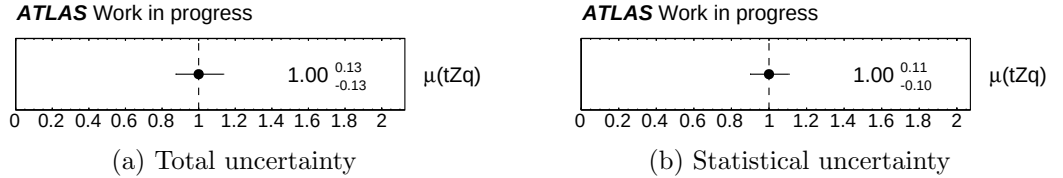


Figure 7.13: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Default** selection using the Binary NN trained splitting regions.

In Figure 7.14 the ranking plot is presented. As expected, the $t\bar{t}Z$ showering impact was reduced from 5% to less than 4%, but nonetheless this remained the systematics with the highest impact. Additionally, we observe a significant constraint, around 0.5, on the tZq showering uncertainty. This constraint is mostly due to the fact that we are splitting the regions based on jet multiplicity. Pull plot and correlation matrix will not be presented, as the only constraint, found on tZq showering, has already been discussed, and the only significant correlation occurred between tZq showering and tZq A14, with a -24% correlation.

In summary, this fit used 3 SRs with 10 bins each, 1 POI and 25 NPs, and the total uncertainty on the POI is $\pm 13\%$. The only NP constrained is the tZq showering, with a 0.5 constraint. Overall, this fit not only performed better than the previous one, as the

uncertainty was reduced from 16% to 13%, but it was also better than the old analysis result of a 15% uncertainty.

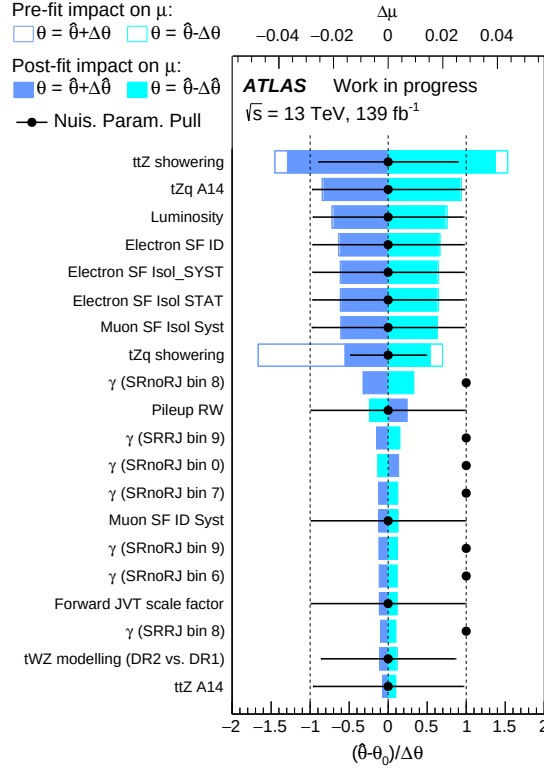


Figure 7.14: NP ranking for the fit with the **Default** selection using the Binary NN trained splitting regions.

MC-4

Following up on the NN trainings performed, we decided to try a fit using the MultiClass trained with 4 classes (Section 6.2.2). The idea behind this is to create regions enhanced in only one background source, so that the systematics regarding said background are improved, resulting in a lower uncertainty. I will present only the fit with the MC-4 setup, because we have seen that it gave better results than the MC-3 one.

3 regions were defined in order to maximise the signal significance $S/\sqrt{S+B}$, and only three NN outputs out of the 4 generated were used, which are the ones for which generating cuts was possible, as they were the NN trained using as targets the sources with more statistics. The three region were defined as in Table 7.2. The tZq SR is the region in the bottom left corner of all plots in Figure 6.15, with cuts on Diboson score at 0.41 and on $t\bar{t}Z$ score at 0.31. The region with Diboson score greater than 0.41 and $t\bar{t}Z$ score lower than 0.31 is the VV CR, whereas the opposite region is the $t\bar{t}Z$ CR. These cuts generate an excluded region, where Diboson is greater than 0.41 and $t\bar{t}Z$ is greater than 0.31, in which 41 events (2 signal) were present. Therefore, the loss in statistics can

be considered as negligible, thus justifying this choice of cuts.

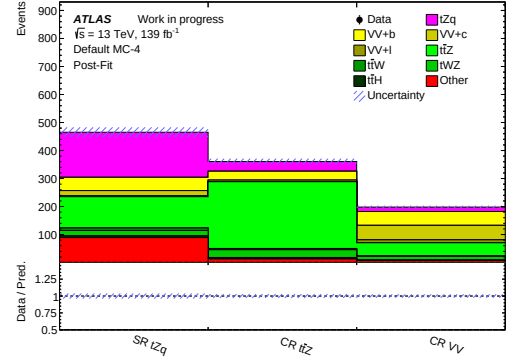
The Control Regions are treated the same as the SRs, as they have a non-negligible signal contribution, as Figure 7.15(b) showcases. Nevertheless, the cuts applied were able to locate the different sources correctly. 76% of all signal events are found in the tZq SR, 60% of $t\bar{t}Z$ is located in the $t\bar{t}Z$ CR and 51% of Diboson is in the VV CR. Because no cuts were applied on the *Others* NN output, the *Others* are found mostly located in the tZq SR, because, as Figure 6.14 displays, the *Others* are found at low values of O_{VV} and $O_{t\bar{t}Z}$.

	SR tZq	CR $t\bar{t}Z$	CR VV
Definition	$O_{VV} < 0.42$ $O_{t\bar{t}Z} < 0.31$	$O_{VV} < 0.42$ $O_{t\bar{t}Z} > 0.31$	$O_{VV} > 0.42$ $O_{t\bar{t}Z} < 0.31$
Jet regions	$njmb$	$njmb$	$njmb$
Number of bins	10	5	4
Variable fitted	O_{tZq}	$O_{t\bar{t}Z}$	O_{VV}
Target contribution	34.6%	66.2%	56.4%
Signal contribution	34.6%	9.6%	7.9%

Table 7.2: Description of the cuts applied to define the three orthogonal regions. $njmb$ refers to $2j1b$, $3j1b$, $4j1b$, $3j2b$ and $4j2b$, whereas the target is tZq in tZq SR, $t\bar{t}Z$ in $t\bar{t}Z$ CR and Diboson in VV CR.

	SR tZq	CR $t\bar{t}Z$	CR VV
tZq	160.9 ± 19.6	34.7 ± 4.3	15.8 ± 2.1
$VV + b$	47.4 ± 1.4	31.6 ± 0.9	49.4 ± 1.4
$VV + c$	19.1 ± 0.6	5.1 ± 0.1	51.7 ± 1.5
$VV + l$	2.7 ± 0.1	0.6 ± 0.0	10.5 ± 0.3
$t\bar{t}Z$	111.8 ± 6.7	238.4 ± 9.1	47.1 ± 1.8
$t\bar{t}W$	8.8 ± 0.3	4.5 ± 0.1	1.6 ± 0.0
tWZ	19.5 ± 2.4	27.7 ± 4.7	13.3 ± 2.0
$t\bar{t}H$	6.1 ± 0.2	5.2 ± 0.2	1.0 ± 0.0
Other	89.0 ± 2.9	12.8 ± 0.4	7.6 ± 0.2
Total	465.2 ± 17.6	360.6 ± 10.3	198.0 ± 4.9

(a) Post-fit SR yields



(b) Summary plot with all regions

Figure 7.15: Post-fit SR yields (left) and summary plot with all regions (right) for the fit with the **Default** selection using the MC-4 NN.

SR and CRs plots are presented in Figure 7.16, where the advantage of using a MultiClass NN can be clearly seen. The tZq SR has almost only signal in the last bins, whereas the opposite is found in the two CRs, where the signal distributions decrease toward the right while the target distributions increase significantly. Because we were able to create a region enriched with $t\bar{t}Z$ we could expect the impact of the $t\bar{t}Z$ showering systematics to drop with respect to the previous two fits. However, since $t\bar{t}Z$ is also found

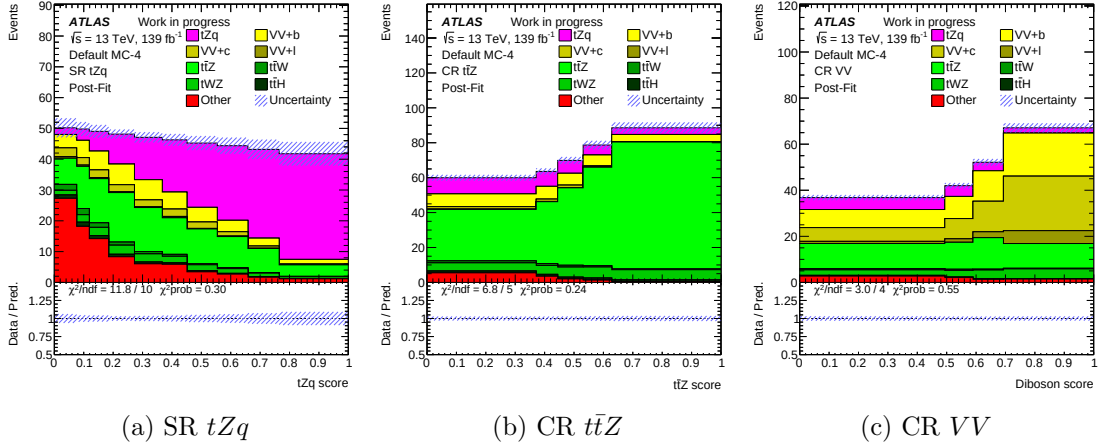


Figure 7.16: Post-fit SR plots for the fit with the **Default** selection using the MC-4 NN.

in the tZq SR with an almost flat distribution, the improvements given by the $t\bar{t}Z$ CR are damped.

The total and stat-only uncertainties are presented in Figure 7.17. The MLE for the POI is $\mu(tZq) = 1.00^{+0.14}_{-0.13} = 1.00^{+0.11}_{-0.10}(\text{stat}) \pm 0.08(\text{syst})$. Among the systematics, the greatest impact comes from the leptons (4.9%), the prompt lepton backgrounds (4.5%) and the luminosity (2.6%). tZq modelling impact is 1.9%, greater than the Binary but smaller than the previous fit. Both total and stat-only uncertainties are greater than the ones obtained fitting the Binary splitting the regions in the training.

The ranking plot of the NPs is presented in Figure 7.18. Once again, the $t\bar{t}Z$ showering is the leading uncertainty, with an impact of little less than 5%, lower than the impact on the Binary NN trained together (Figure 7.9(a)) but greater than the Binary NN trained separately (Figure 7.14). The tZq uncertainties' contribution significantly dropped with respect to the previous training, especially the tZq A14, which went from second to eighth, whereas the tZq showering did not present any pull, because the regions definition was not based on jet multiplicity. Moreover, no systematics reported a significant constraint.

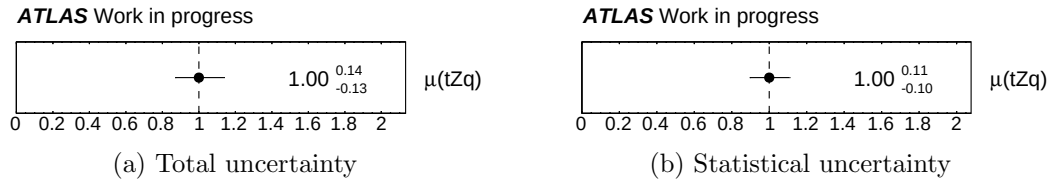


Figure 7.17: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Default** selection using the MC-4 NN.

To summarise this fit, we used 3 regions with 10, 5 and 4 bins respectively, fitting in each one the NN output of the target which contributed more to that region. Once again, 1 POI and 25 NPs were defined, and the total uncertainty on the POI turned out to be +14%, -13%, greater than the one obtained from the previous fit but still lower

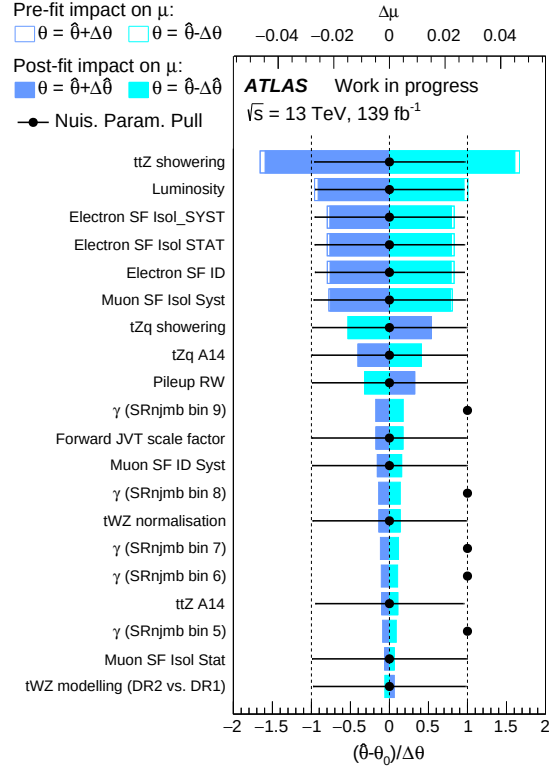


Figure 7.18: NP ranking for the fit with the `Default` selection using the cuts on the outputs of the MC-4 NN.

than both the old analysis and the first fit, made by fitting one SR with the Binary NN.

7.2.2 Loose selection

The fits with the **Default** selection allowed to improve the cross section uncertainty, thus resulting in a fit which returned better results than the old analysis. Nevertheless, because we are using only a small set of uncertainties in the fits shown so far, we expect the total uncertainty to be higher when we include the full set. Therefore, in order to improve even more the inclusive cross section total uncertainty, we decided to perform the fits using the **Loose** selection as well, since the NN training performance was improved with respect to **Default**. Furthermore, because the **Loose** selection has a higher statistics, having almost three times the event yields of the **Default** selection, the statistical uncertainty will be reduced as well, and this will lead to an even greater improvement in the total uncertainty, since this process is dominated by statistics.

The same setup of the fits with the **Default** selection was used. Similarly to what was done with the **Default** selection, I will begin by presenting a Binary fit, followed by a Multi Class with 3 classes.

Binary

The first fit I am presenting with the **Loose** selection is the one in which a fit was made to the NN output, whose training is described in Section 6.3.1. This training was, among the Binary NNs trained with all regions together, the best one. Following the same steps as **Default**, this fit has 1 SR, in which the jet regions *2j1b*, *3j1b*, *4j1b*, *3j2b* and *4j2b* are included, 1 POI and 25 NPs.

The SR plot is presented in Figure 7.19. As discussed in Section 6.3.1, this NN has not been able to correctly treat the $t\bar{t}Z$ background, as its distribution is quite flat, whereas Diboson and Fakes distributions have a background-like shape. This is highlighted in Figure 7.19, where the use of the **Autobin** function evidences that the Fakes are all located in the lowest values (less than 0.05) of the NN output, Diboson peaks before 0.1 whereas $t\bar{t}Z$ is quite flat up until 0.7, when it finally decreases. The signal on the other hand has the expected shape, with more than 70 events in the bin with $O_{NN} > 0.95$.

In Figure 7.20 both the total and the stat-only uncertainties are presented. The MLE for the POI is $\mu(tZq) = 1.00^{+0.13}_{-0.12} = 1.00^{+0.10}_{-0.09}(\text{stat})^{+0.08}_{-0.07}(\text{syst})$. The greatest contribution to the systematic uncertainty comes from the signal modelling, in particular the A14, at 5%, followed by leptons at 3.5% and MC statistics at 2.1%. Prompt-lepton background contributes for 2%, due mostly to the $t\bar{t}Z$ showering, whereas luminosity's impact is 1.6%. Overall, this uncertainty is the lowest in total, statistical and systematics among the fits shown so far. Moreover, all systematics contribution but the A14 one have decreased, with leptons, showering and luminosity all halving their impact.

The NP ranking plot is presented in Figure 7.21. We can see that the increase in the ISR contribution comes tZq A14, since $t\bar{t}Z$ A14 contributes less than 0.5%, whereas the leptons' impact is given mostly by the same four systematics, regarding electron isolation and ID and muon isolation. Moreover, the Pileup RW systematics is now the third highest

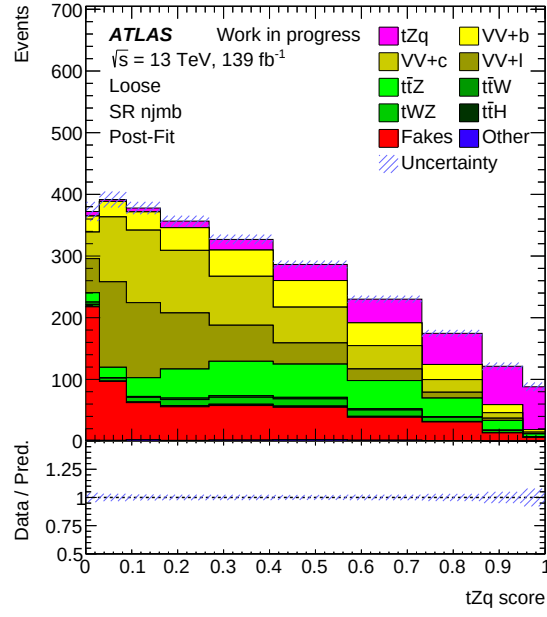


Figure 7.19: Post-fit SR plot displaying the Binary NN output distribution with the **Loose** selection.

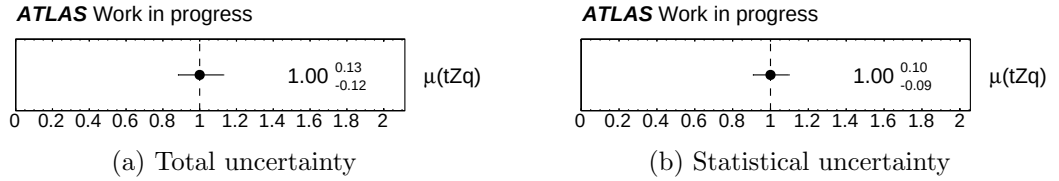
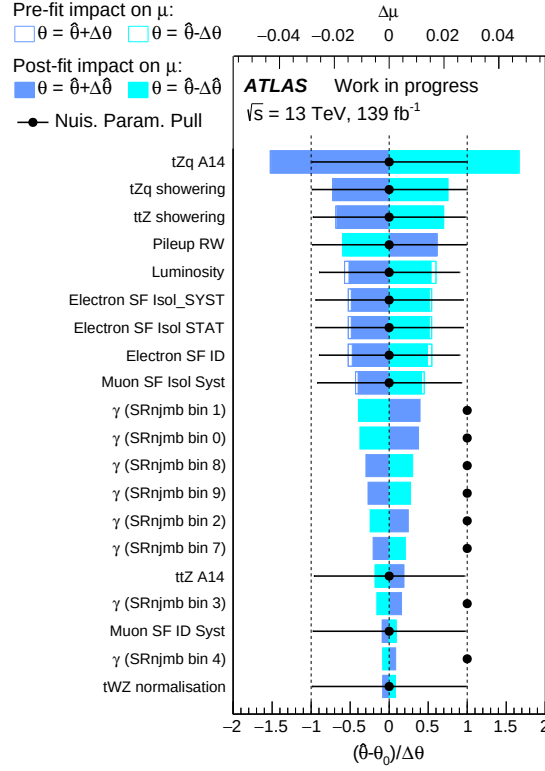


Figure 7.20: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Loose** selection using the Binary NN.

ranked, one step above luminosity, whereas for the **Default** Binary NN (Figure 7.9(a)) it was the ninth highest. Furthermore, no significant pulls or correlations between systematics are present.

In summary, this fit used only 1 SR with 10 bins, in which the Binary NN output trained on the **Loose** selection has been fitted. 1 POI and 25 NPs were included, and the total uncertainty on the POI turned out to be +13%, −12%, resulting in this fit being the one with the lowest overall uncertainty.


 Figure 7.21: NP ranking for the fit with the **Loose** selection using the Binary NN.

MC-3: $t\bar{t}Z$

Same as we did for the **Default** selection with the Multi Class, we tried to apply cuts to the NN outputs in order to generate regions in which ideally only one background contributed. However, with the **Loose** selection we used a Multi Class with 3 classes: signal, $t\bar{t}Z$ and *Others*, whose training performance can be found in Section 6.3.2. The *Others* category includes Diboson, Fakes, tWZ , $t\bar{t}H$, $t\bar{t}W$, and small contributions from 3 and 4 *top* quarks production.

We followed the same idea applied to the **Default** MC-4 fit, and we defined the tZq SR as the region which maximised the signal significance $S/\sqrt{S+B}$. As Figure 6.20 displays, the highest signal significance is 9.24, obtained when $O_{t\bar{t}Z} = 0.44$ and $O_{Others} = 0.18$. Therefore, the SR is defined as the region with output values lower than those two, as represented in Table 7.3. Because the Diboson and Fakes response is more localised in the region with high *Others* score, as opposed to $t\bar{t}Z$ which is more spread, the $t\bar{t}Z$ CR was defined with $O_{t\bar{t}Z} > 0.44$ and no cuts on the *Others* score, in order to be as inclusive as possible. Consequently, the *Others* CR was defined as the region orthogonal to the two, thus not losing statistics by removing a region, as we did for the **Default** MC-4.

As Figure 7.22 displays, these regions are more pure than the ones obtained with the **Default** MC-4. 55% of the total signal events are located in the tZq SR, accounting for 45% of the total yields in that region, an improvement with respect to the 35% of the

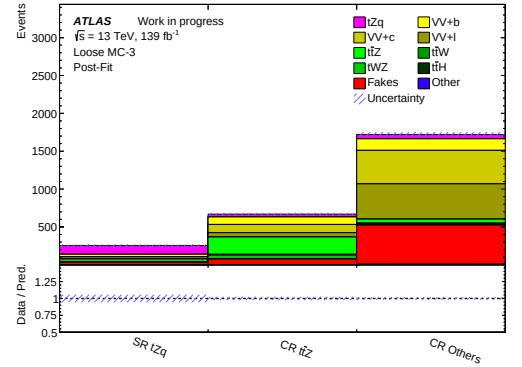
	SR tZq	CR $t\bar{t}Z$	CR $Others$
Definition	$O_{t\bar{t}Z} < 0.44$ $O_{Others} < 0.18$	$O_{t\bar{t}Z} > 0.44$ -	$O_{t\bar{t}Z} < 0.44$ $O_{Others} > 0.18$
Jet regions	n_{jmb}	n_{jmb}	n_{jmb}
Number of bins	10	10	10
Variable fitted	O_{tZq}	$O_{t\bar{t}Z}$	O_{Others}
Target contribution	45.3%	34.2%	93.7%
Signal contribution	45.3%	5.5%	3.2%

Table 7.3: Description of the cuts applied to define the three orthogonal regions. n_{jmb} refers to $2j1b$, $3j1b$, $4j1b$, $3j2b$ and $4j2b$, whereas the target is tZq in tZq SR, $t\bar{t}Z$ in $t\bar{t}Z$ CR and $Others$ in $Others$ CR.

Default selection. Furthermore, the signal contribution is 5.5% and 3.2% in the CRs $t\bar{t}Z$ and $Others$, respectively, with the latter region having only 109 events, 6% of the total, not belonging to the $Others$ target.

	SR tZq	CR $t\bar{t}Z$	CR $Others$
tZq	115.2 ± 15.3	37.0 ± 5.5	55.6 ± 7.5
$VV + b$	30.5 ± 0.7	98.9 ± 2.4	152.8 ± 3.3
$VV + c$	23.6 ± 0.6	108.4 ± 2.5	442.1 ± 9.4
$VV + l$	9.0 ± 0.3	57.2 ± 1.3	465.7 ± 10.5
$t\bar{t}Z$	32.3 ± 4.0	229.1 ± 14.3	53.3 ± 3.4
$t\bar{t}W$	1.6 ± 0.0	10.3 ± 0.3	5.9 ± 0.1
tWZ	7.6 ± 0.9	45.1 ± 5.7	17.0 ± 2.2
$t\bar{t}H$	1.0 ± 0.0	7.3 ± 0.2	2.6 ± 0.1
Fakes	31.9 ± 1.0	72.3 ± 2.2	517.5 ± 13.9
Other	1.5 ± 0.1	3.1 ± 0.1	6.8 ± 0.2
Total	254.3 ± 14.3	668.6 ± 17.0	1719.4 ± 32.1

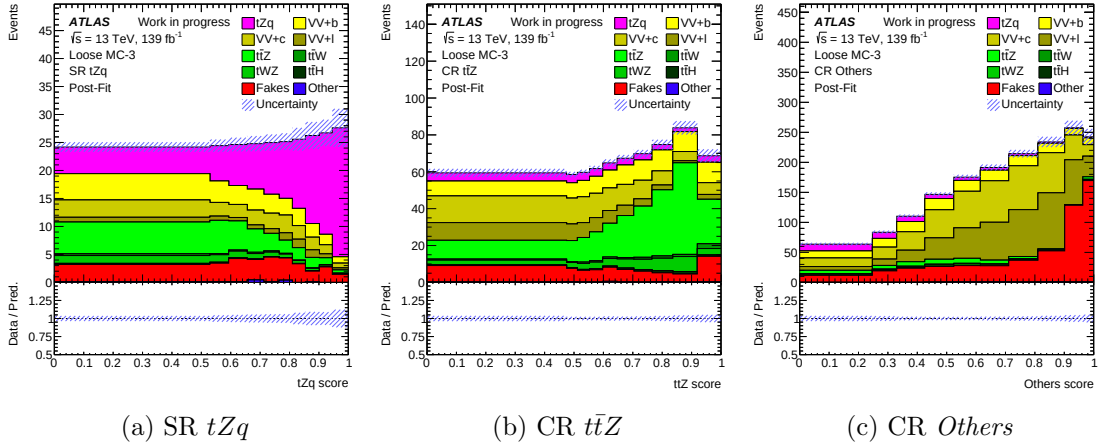
(a) Post-fit SR yields



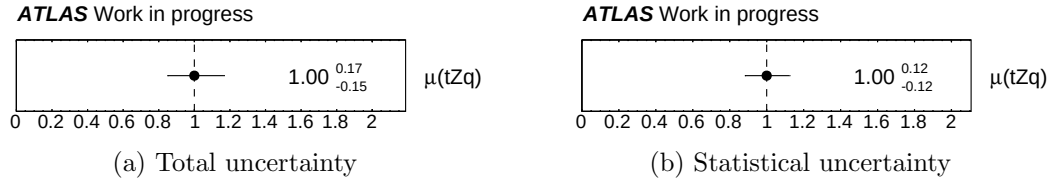
(b) Summary plot with all regions

Figure 7.22: Post-fit SR yields (left) and summary plot with all regions (right) for the fit with the **Loose** selection using the $t\bar{t}Z$ MC-3 NN.

SR and CRs plots are shown in Figure 7.23, and once again we can see the improvement with the use of a Multi Class with respect to the Binary. Not only we are able to generate different regions enhanced in different backgrounds, but we also have the distributions in the regions well separated between the different contributions. Only the $t\bar{t}Z$ CR does not have its target ($t\bar{t}Z$) peaking in the last bin, whereas the tZq SR and especially the $Others$ CR have their target peaking at high values of their respective score. In the former, 25 signal events are found in the last bin, out of a total of 28, whilst in the latter out of the 240 events in the final bin, only 20 are not Fakes or Diboson, which are the two sources contributing the most in the region. Once again, the CRs are treated the same as the SRs, since the signal contribution is not negligible.


 Figure 7.23: Post-fit SR plots for the fit with the Loose selection using the $t\bar{t}Z$ MC-3 NN.

The total and the stat-only uncertainty on the POI are presented in Figure 7.24, with the MLE for the POI being $\mu(tZq) = 1.00^{+0.17}_{-0.15} = 1.00 \pm 0.12(\text{stat})^{+0.11}_{-0.09}(\text{syst})$. Surprisingly, this uncertainty was higher than the one obtained with the Binary fit, in contrast with what we have seen with the Default selection. Among the systematics, signal modelling, leptons and MC statistics are the ones with the highest impact to the total uncertainty, respectively at 7.2%, 4.6% and 3.1%, all increased with respect to the Binary fit. On the other hand, prompt-lepton background modelling and luminosity's impacts stayed the same.


 Figure 7.24: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the Loose selection using $t\bar{t}Z$ MC-3.

The deterioration of the fit is most likely to be attributed to the shape of the $t\bar{t}Z$ score distribution in the $t\bar{t}Z$ CR. The Fakes have a small peak in the last bin, where theoretically they should not be found, whereas tZq and the tree Diboson samples remain flat throughout the plot. The main problem is however the $t\bar{t}Z$ background, which halves from the 9th to the last bin, and its non-regular shape does not help the fit.

The NP ranking plot is displayed in Figure 7.25. We can see how both showering uncertainties have increased significantly, with the tZq showering being the leading one with a 5.5% impact on the POI. Moreover, a small constrained is present for this systematics as well, but the constraint is less than 0.9, so this is no real cause of concern.

To summarise this fit, we have used 3 regions with 10 bins each, in which we have fitted the NN output corresponding to the source that was more present in the region. 1

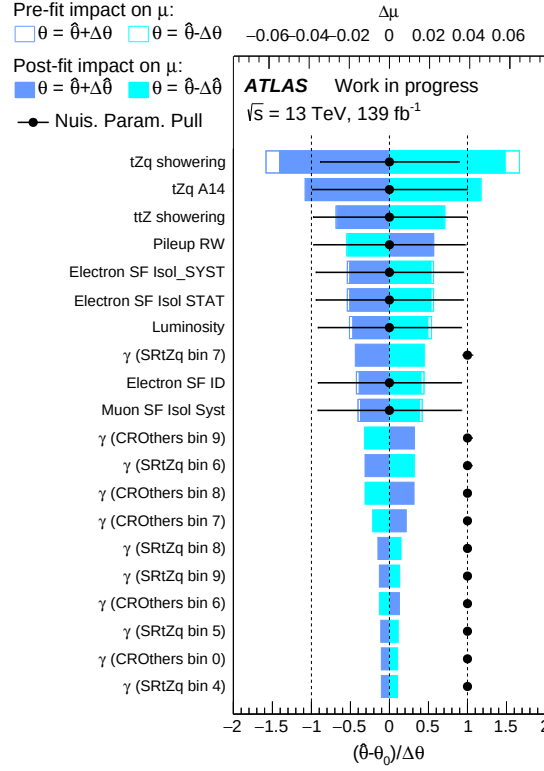


Figure 7.25: NP ranking for the fit with the **Loose** selection using the $t\bar{t}Z$ MC-3 NN.

POI and 25 NPs were included, and the total uncertainty on the POI returned by the fit is +17%, −15%, thus making this fit better only than the **Default** Binary fit (Figure 7.8), also worse than the old analysis result. More investigation would have been required in order to understand the deterioration of this fit, even if multiple attempts at a different region definition were performed with no improvements. However, after testing one fit with the **Medium** selection, we realised that this region looked more promising for the fits, since it has more statistics and a higher signal significance. Therefore, we dropped the **Loose** selection and focused only on the **Medium**.

7.2.3 Medium selection

Finally, I will present the fits performed with the **Medium** selection. The **Loose** selection's Binary fit performed better than both **Default** and the old analysis, but the uncertainty was still more than 12%, which is worse than the 11.5% uncertainty obtained by tZq 's most recent measurement performed by CMS [61], which is the uncertainty target of this analysis. Furthermore, this fits are not performed with all the systematics, therefore our total uncertainty will increase once the complete set of systematics is used. Consequently, we decided to try a new event selection, the **Medium** selection, whose definition and yields are reported in Tables 4.5 and 4.6.

As aforementioned, this region is the region with the highest statistics, almost three

times more than **Default** and almost 10% more than **Loose**, as well as the highest signal yields, 30 events more than **Loose** and 115 more than **Default**. Moreover, the signal significance $S/\sqrt{S+B}$ is improved with respect to the **Loose** selection. All these effects are due to both a looser jet p_T threshold and an increase in jet multiplicity, with the addition of 5-jets events.

Furthermore, since we started doing fits with this event selection after the ATLAS' announcement of the new luminosity measurement, all these next fits are performed with an integrated luminosity of $140 \pm 1.2 \text{ fb}^{-1}$, as the labels in the plots remind us.

Similarly to what was done with the previous two selections, we used the **Autobin** function, performing blind fits with the same set of systematics. I will begin with the presentation of the attempts made at using the Binary NN output, either trained on all regions or on subset, followed by fits using the different Multi Classes. With respect to the previous two selections, more fits will be presented, since also a Multi Class with VV and using the Lorentz invariant variables were tested.

Binary

The first fit I am presenting is once again the simplest one, with only one SR in which the Binary NN output, whose training specifics can be found in Section 6.4.1, was fitted. However, this time the SR includes 7 jet regions, which are $2j1b$, $3j1b$, $4j1b$, $5j1b$, $3j2b$, $4j2b$ and $5j2b$.

The NN training performance was a bit deteriorated with respect to **Loose** Binary NN, with a separation lowered by 3%, as displayed in Figure 6.24(a). Moreover, the classifier was not able to treat correctly the $t\bar{t}Z$ background, as it does not peak in the first bins as Diboson and Fakes do. Nonetheless, the SR plot in Figure 7.26 looks promising, as it has almost 280 Fakes events in the first bin ($O_{tZq} < 0.07$), whereas toward greater values of the tZq score we have almost only signal.

Total and stat-only uncertainties are reported in Figure 7.27. The MLE for the POI returned $\mu(tZq) = 1.00^{+0.12}_{-0.11} = 1.00 \pm 0.09(\text{stat}) \pm 0.07(\text{syst})$, with the greatest contribution from the systematics given by the leptons (4.6%) and both prompt-lepton background (3.7%) and signal (3.3%) modellings. This result is the best obtained so far, being the only one with $\pm 9\%$ statistical uncertainty and $\pm 7\%$ in systematics. Furthermore, the new luminosity measurement reduced significantly the luminosity impact, which in this fit is only 0.9%.

The NP ranking plot is presented in Figure 7.28. The two showerings and the tZq A14 are the three leading systematics, but none of them reports any constraint. Once again, this was expected for the tZq showering, because no splitting between regions with different jet multiplicity was implemented. Moreover, we can see the reduced impact of the luminosity, which is now the 13th highest systematics, whereas the same three leptons systematics still occupy the highest spots in the ranking. Furthermore, no significant pulls or correlations between systematics are present.

In summary, this fit, performed with only 1 SR in which the Binary NN output of

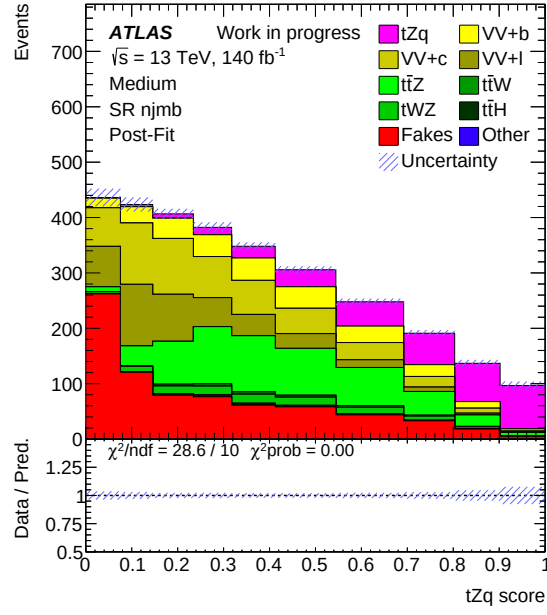


Figure 7.26: Post-fit SR plot displaying the Binary NN output distribution with the **Medium** selection.

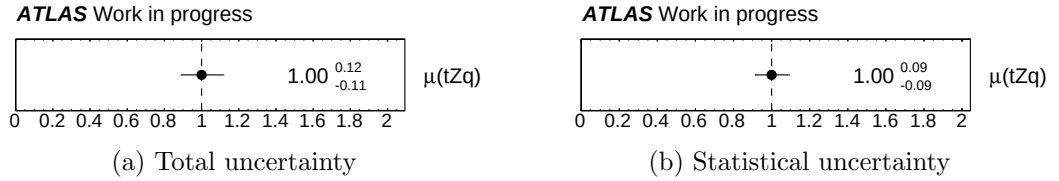


Figure 7.27: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Medium** selection using the Binary NN.

the **Medium** selection was fitted, using 1 POI and 25 NPs, reported a total uncertainty on the POI of +12%, −11%, thus being the best fit performed so far, especially in comparison with the other two Binary fits. Therefore, we decided to test multiple configurations with this selection, as it looked more promising than the other two.

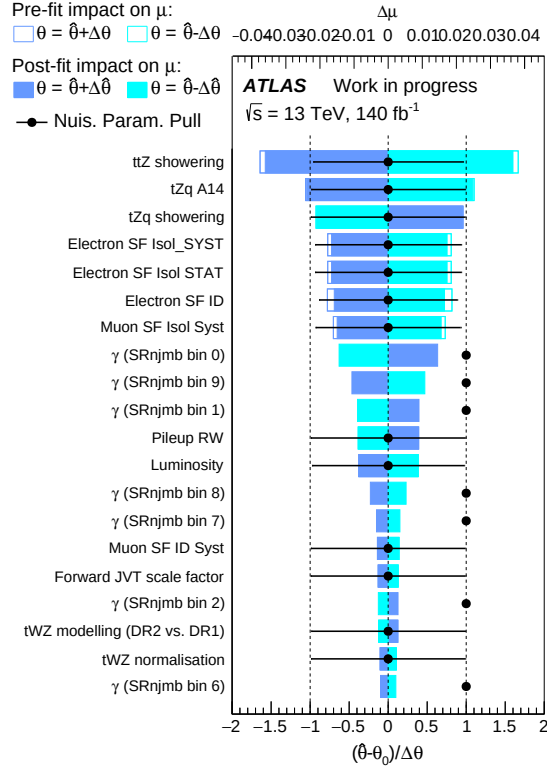


Figure 7.28: NP ranking for the fit with the **Medium** selection using the Binary NN.

Binary splitting regions in fit

After seeing that the fit using the Binary NN with the **Medium** selection performed better than its counterpart with **Default** and **Loose**, we decided to test a more complex configuration with the same NN. Ideally, one would train each jet region separately, and then fit the NN output trained in each region separately. However, some regions do not have enough statistics to be trained properly. Therefore, we tried two different roads. The first one is splitting the regions based on whether they had a radiation jet or not, additionally splitting the RJ region in number of b -jets, as presented in Figure 6.27, and those fits will be reported later on. The other road implies using the Binary NN trained with all regions together, which is the same one used for the fit shown above, and perform a fit using 7 different SRs, defined by jet and b -jet multiplicity. The idea with this fit is that we can create regions in which mostly one type of background is present, since different jet regions are usually associated with a specific set of background, without needing to use a Multi Class, which is usually poorer on separating the different sources than a Binary NN. For future references, this fit will be also called **Binary-SRs**, in order to differentiate it with the one in which the regions are split also in the training.

The post-fit yields in all the 7 SRs are shown in Figure 7.29. The $2j1b$ alone accounts for more than a third of all the statistics, as well as 31% of the total signal events. We can also see how Diboson and Fakes events are more likely to have 1 b -jet instead of 2, which

7.2. FIT: SMALL SET OF SYSTEMATICS

	SR 2j1b	SR 3j1b	SR 4j1b	SR 5j1b	SR 3j2b	SR 4j2b	SR 5j2b
tZq	101.0 ± 12.2	87.5 ± 8.9	42.8 ± 5.5	13.5 ± 2.2	35.1 ± 3.5	32.1 ± 3.9	14.3 ± 2.1
$VV + b$	97.6 ± 2.1	71.4 ± 1.5	41.3 ± 0.9	19.0 ± 0.5	17.7 ± 0.4	13.7 ± 0.3	8.2 ± 0.2
$VV + c$	230.9 ± 5.1	152.5 ± 3.5	80.5 ± 1.9	35.9 ± 1.0	11.2 ± 0.3	8.2 ± 0.2	5.2 ± 0.1
$VV + l$	188.8 ± 4.3	123.6 ± 3.1	63.5 ± 1.7	28.7 ± 0.9	3.1 ± 0.1	2.7 ± 0.1	1.5 ± 0.0
$t\bar{t}Z$	39.6 ± 3.0	84.3 ± 4.9	91.1 ± 3.4	63.8 ± 3.0	73.1 ± 5.6	109.1 ± 5.6	88.8 ± 2.3
$t\bar{t}W$	5.2 ± 0.1	3.8 ± 0.1	2.0 ± 0.0	1.1 ± 0.0	5.1 ± 0.1	3.0 ± 0.1	1.6 ± 0.0
tWZ	16.2 ± 1.7	24.7 ± 2.9	19.4 ± 2.8	10.4 ± 1.7	8.0 ± 1.2	10.5 ± 2.3	8.0 ± 2.3
$t\bar{t}H$	1.6 ± 0.0	2.6 ± 0.1	2.6 ± 0.1	1.8 ± 0.0	2.8 ± 0.1	3.3 ± 0.1	2.8 ± 0.1
Fakes	400.6 ± 11.9	196.6 ± 6.2	74.3 ± 2.0	31.8 ± 1.1	28.2 ± 0.9	18.6 ± 0.6	7.2 ± 0.2
Other	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.0	0.0 ± 0.0	0.1 ± 0.0	0.1 ± 0.0
Total	1081.7 ± 23.3	746.9 ± 15.7	417.4 ± 9.4	206.0 ± 5.9	184.3 ± 6.2	201.3 ± 6.4	137.6 ± 3.6
Signal	9.3%	11.7%	10.3%	6.6%	19.0%	15.9%	10.4%
$S/\sqrt{S+B}$	3.07	3.20	2.09	0.94	2.59	2.26	1.22

Figure 7.29: Post-fit yields in the 7 SRs.

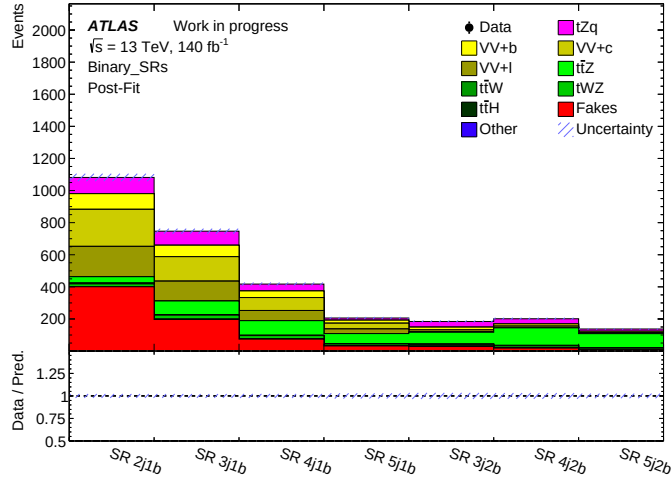


Figure 7.30: Summary plot with all the regions

instead is where the $t\bar{t}Z$ background is located. In particular, in the $5j2b$ SR, $t\bar{t}Z$ accounts for 64% of the total yields, with the signal making up for a mere 10%. The region with the highest signal significance is $3j1b$, followed by $2j1b$, whereas the $5j1b$ has the lower $S/\sqrt{S+B}$ at 0.94.

Post-fit plots for all SRs are presented in Figure 7.31. We can see how, in spite of the training being made with all regions together, we have a good separation in all regions. Moreover, the plots represent better the aforementioned advantage of this fit, because we can see that we have the 1 b -jet regions enriched with Fakes and Diboson, whereas the 2 b -jets regions contain for the most $t\bar{t}Z$. And especially the 2 b -jets regions can be useful for the fit, since the separation between signal and $t\bar{t}Z$ is almost perfect, with the latter decreasing constantly as the tZq score increases.

The MLE for the POI is $\mu(tZq) = 1.00^{+0.11}_{-0.10} = 1.00 \pm 0.09(\text{stat}) \pm 0.06(\text{syst})$, as displayed by Figure 7.32. The systematic uncertainty is dominated by leptons uncertainties (4.4%), followed by prompt-lepton background and signal modelling, at 2.7% and 2.4%.

Overall, this is the best fit obtained so far, since it is the first one whose systematics uncertainty is $\pm 6\%$, whereas the statistical uncertainty is the same as the Binary NN in Figure 7.27. With respect to that same training, it is interesting to note that the showering contribution has been halved, even if we expect to have some constraints on the tZq showering uncertainty, because the regions were defined by splitting the different jet regions.

In Figure 7.33 it is displayed the NP ranking for this fit. The constraint on the tZq showering is evident, with a constraint of 0.35. This is also displayed by the fact that the post-fit impact on μ is much different than the pre-fit one, especially for the negative variation. As aforementioned, this was expected, since the plot in Figure 7.3(b) refers to this fit, in the $2j1b$ SR. Therefore, being the uncertainty so high, we expected to see this constraint. No other constraints were found, whereas, similar to what was observed in the Binary NN splitting regions in the training using the `Default` selection, we observe a strong anti-correlation between tZq showering and A14, of -41.3% , almost twice as much as the correlation observed before.

In summary, this fit is the most complex one among the ones we've tested, as it has 7 SRs with 10 bins each, thus meaning that we are giving much more information to the fit. As usual, 1 POI and 25 NPs were used, and the total uncertainty of the POI resulted in $+11\%$, -10% . This is the best fit we have implemented so far.

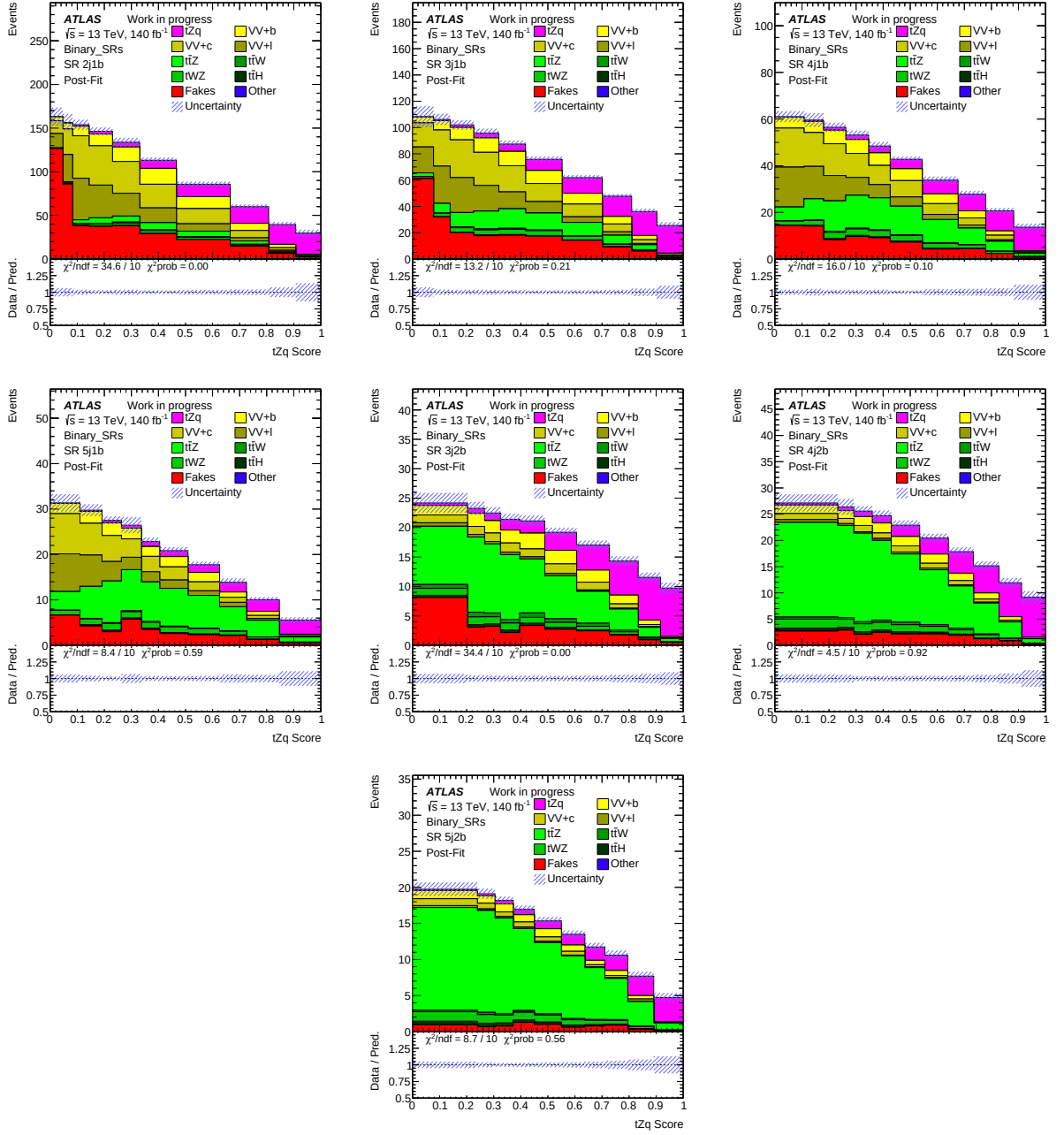


Figure 7.31: Post-fit SR plots for the fit Binary-SRs fit.

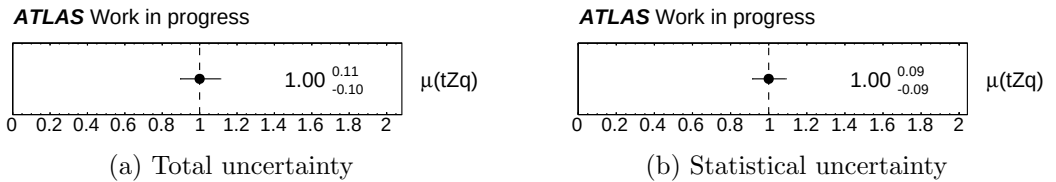


Figure 7.32: POI total uncertainty (left) and stat-only uncertainty (right) for the Binary-SRs fit.

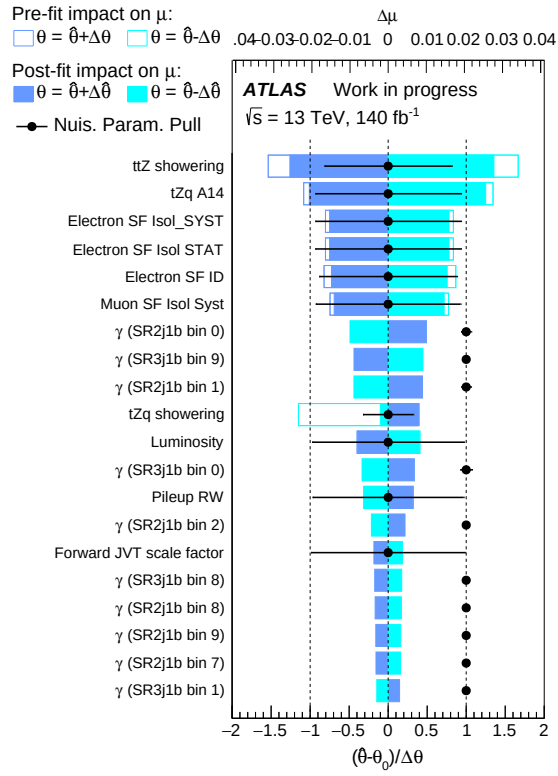


Figure 7.33: NP ranking for the Binary-SRs fit.

Binary splitting regions in training

The other road to improve the Binary training was to split the regions also in the training. As Section 6.4.1 discusses, this training provided the better separation among the different tests we made in the **no-RJ** region. On the other hand, the separation in the other two regions was worse than it was for the training with all regions. Nevertheless, the deterioration in the **RJ+1b** region was negligible with respect to the gain of splitting the regions in the fit. To discriminate this fit from the **Binary-SRs** fit, this fit will also be labelled as **Binary-3** since three different Binary NN were implemented.

With respect to the similar fit performed with the **Default** selection (Table 7.1), this time the fit is expected to perform even better, because we have trained a Binary NN also in all the three regions we used for the fit, therefore we can fit the NN output in all the regions. The definition of the regions is presented in Table 7.4, whereas yields and summary are reported in Figure 7.34. We can see how the first two regions, **no-RJ** and **RJ+1b**, are the two with the most statistics, which reflects the results we have seen in the training. Moreover, we observe the same situation we had seen with the **Default** selection, since the **1b** region is dominated by Diboson and Fakes whereas $t\bar{t}Z$ accounts for almost 60% of the yields in the **RJ+2b** region. Furthermore, 56% of the Fakes are located in the **no-RJ** region, mostly due to the $2j1b$ region, with only 3% of them going in the **RJ+2b** region, because of such a high jet and b -jet multiplicity. The signal is almost equally split between the first two regions, with only 14% located in the other region.

	SR no-RJ	SR RJ+1b	SR RJ+2b
Jet regions	$2j1b, 3j2b$	$3j1b, 4j1b, 5j1b$	$4j2b, 5j2b$
Number of bins	10	10	10
Variable fitted	O_{tZq}^{no-RJ}	O_{tZq}^{RJ+1b}	O_{tZq}^{RJ+2b}

Table 7.4: SR definition for the **Binary-3** fit.

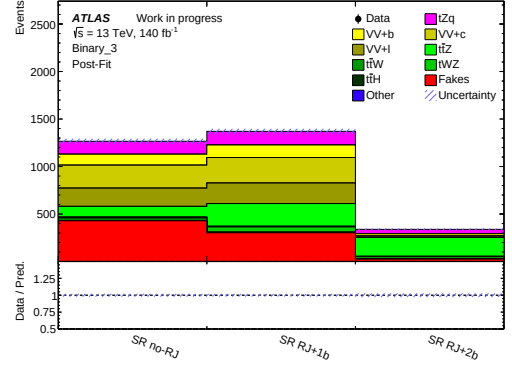
In Figure 7.35 the SR plots are reported. The **no-RJ** is less clean for signal than it was with the **Default** selection (Figure 7.12(a)), whereas in the third region we have a purer $t\bar{t}Z$ region. Furthermore, in spite of two of the three NNs performing worse than the one trained together, we still have regions in which the signal and the backgrounds have the expected shape. Therefore, we can expect better results than that fit.

As a matter of fact, we observe an improvement with respect to the Binary fit trained all together (Figure 7.8), whereas the results are comparable with the ones obtained with the **Binary-SRs** fit. The MLE for the POI is $\mu(tZq) = 1.00^{+0.11}_{-0.10} = 1.00 \pm 0.09(\text{stat}) \pm 0.06(\text{syst})$. Similarly, the systematics with the greater impact are the leptons at 4.2%, the prompt-lepton background modelling at 2.8% and the signal modelling at 2.3%, comparable to **Binary-SRs**.

The NP ranking plot, displayed in Figure 7.37, is almost the same as **Binary-SRs**, with the exception of the tZq showering and the luminosity, which have switched places. Furthermore, even if the jet regions splitting is less evident than it was for **Binary-SRs**,

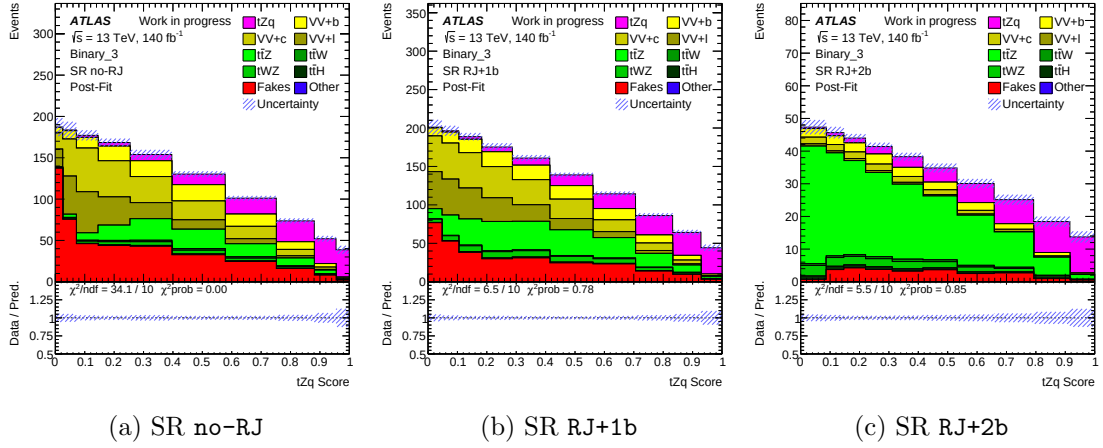
	SR no-RJ	SR RJ+1b	SR RJ+2b
tZq	136.2 ± 15.3	143.7 ± 15.9	46.4 ± 5.8
$VV + b$	115.3 ± 2.4	131.7 ± 2.7	21.9 ± 0.5
$VV + c$	242.1 ± 5.4	268.8 ± 5.7	13.4 ± 0.3
$VV + l$	191.9 ± 4.6	215.8 ± 5.0	4.1 ± 0.1
$t\bar{t}Z$	112.7 ± 9.0	239.2 ± 7.2	197.9 ± 7.7
$t\bar{t}W$	10.3 ± 0.2	7.0 ± 0.1	4.6 ± 0.1
tWZ	24.2 ± 2.8	54.4 ± 7.3	18.5 ± 4.7
$t\bar{t}H$	4.4 ± 0.1	7.0 ± 0.1	6.1 ± 0.1
Fakes	428.9 ± 12.0	302.7 ± 7.7	25.7 ± 0.7
Other	0.0 ± 0.0	0.1 ± 0.0	0.2 ± 0.0
Total	1266.0 ± 26.4	1370.3 ± 26.2	338.9 ± 9.2

(a) Post-fit SR yields



(b) Summary plot with all regions

Figure 7.34: Post-fit SR yields (left) and summary plot with all regions (right) for the Binary-3 fit.



(a) SR no-RJ

(b) SR RJ+1b

(c) SR RJ+2b

Figure 7.35: Post-fit SR plots for the Binary-3 fit.

these regions are still split based on similar properties for the jets. Therefore, we observe a constraint of around 0.35 for this fit as well, as well as an anti-correlation of -43.4% between tZq showering and A14. Once again, no other constraints were found.

To summarise this fit, we have used 3 SRs with 10 bins each, with 1 POI and 25 NPs. The total uncertainty on the POI is +11%, -10%, thus resulting in this fit being slightly better than the **Binary-SRs** fit. However, we cannot state that we are that sensitive to the uncertainty to have a precision of 0.01%, therefore we should treat these two fits as equal, and then see when we apply the full set of systematics which one returns the lowest uncertainty.

With this fit, the section dedicated to the fits using the Binary NN is completed. In the following I will describe the fits performed using the Multi Classes NNs, whose trainings are described in Section 6.4.2.

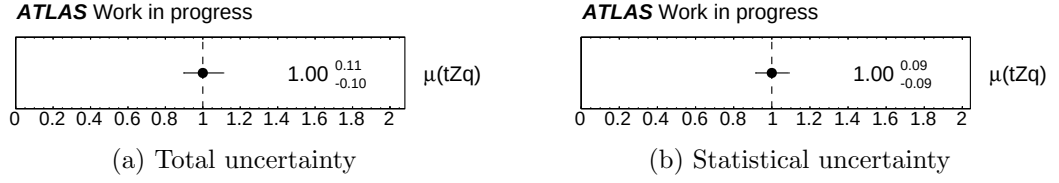


Figure 7.36: POI total uncertainty (left) and stat-only uncertainty (right) for the Binary-3 fit.

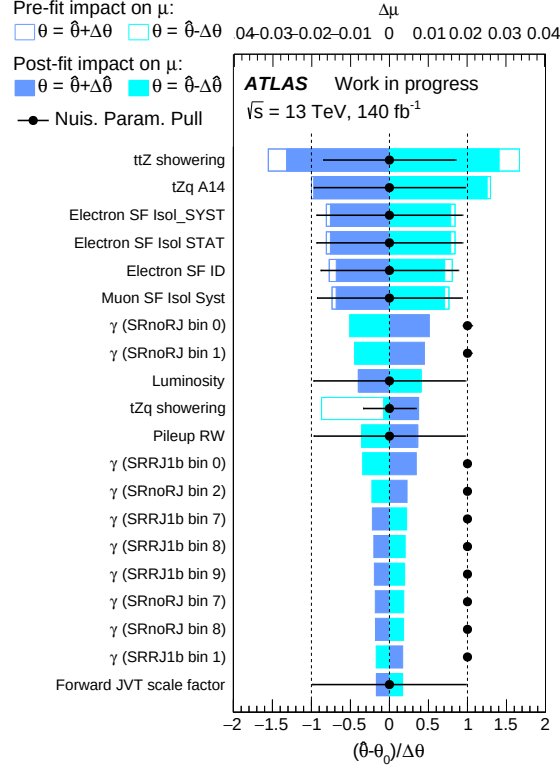


Figure 7.37: NP ranking for the Binary-3 fit.

Lorentz invariant variables: MC-3 VV

I will begin the presentation of the fits using Multi Classes starting from the Lorentz invariant variables, in particular with the MC-3 with signal, *VV* and *Others* as targets. The NN training for this Multi Class is presented in Section 6.4.2.

The 2D plots in Figure 6.30 display immediately a problem with this training, which has also been already discussed above. The $t\bar{t}Z$ response is too spread in the plane to define a $t\bar{t}Z$ and Fakes CR, especially since there are two small peaks in the $t\bar{t}Z$ distribution, one where the signal is located and one where Diboson is located. Moreover, the signal distribution is quite spread as well, therefore also the definition of a signal region would not be possible. Consequently, even if this fit uses a Multi Class NN, we decided to perform the fit using only one region, in which the tZq NN output was fitted. This is not the first time we tested this setup, since also for the Default selection we tried a similar

configuration, even if that fit was not shown. With this setup, we lose the advantage of using a Multi Class, because we do not generate different regions, and we also fit a NN whose separation is usually worse than Default. Nonetheless, because in a MC the outputs are set so that their sum equals 1, by fitting only the tZq score we are still able to locate a good amount of signal and few of the backgrounds in the regions where $O_{tZq} > 0.9$, which is where $O_{VV} + O_{Others} < 0.1$. For the **Default** selection we observed a significant improvement with respect to the Binary NN, whereas in comparison with the fit applying cuts we found a small deterioration, since the total uncertainty for this fit was $+0.14$, -0.13 . Therefore, since we cannot perform a fit applying cuts, this fit setup I will be presenting is the best alternative, which can still provide acceptable results. Nevertheless, we expect the results of this fit to be worse than the ones obtained performing the fit using the standard variables, since their NN performance was better.

As aforementioned, we have only one SR, which is presented in Figure 7.38. We can see how, in spite of a low overall separation, we are still left with a final bin in which we have twice as much signal (80 events) than backgrounds (40). Fakes and especially Diboson are well separated, as also the 2D plots (Figure 6.30) told us, whereas the $t\bar{t}Z$ distribution stays almost flat until $O_{tZq} \simeq 0.6$.

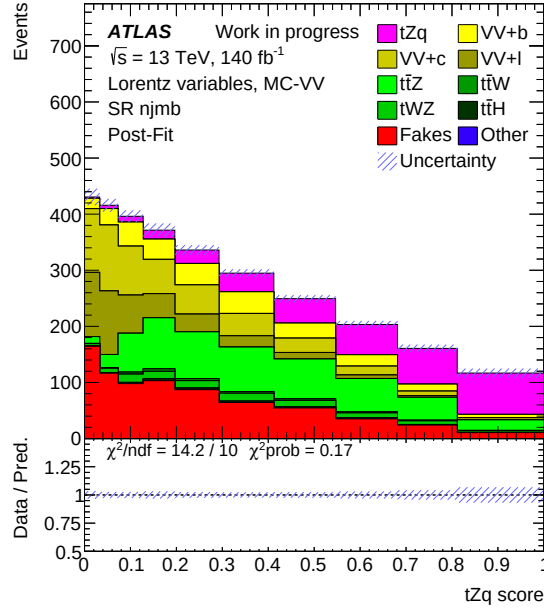


Figure 7.38: Post-fit SR plot displaying the tZq output distribution with the **Medium** selection using the MC-3 VV with Lorentz invariant variables NN.

With respect to the Binary NN, we observed a deterioration in the fit. The MLE for the POI is $\mu(tZq) = 1.00 \pm 0.13 = 1.00 \pm 0.10(\text{stat}) \pm 0.09(\text{syst})$, with both statistical and systematics uncertainties greater than the ones for the Binary. Analogously, the leptons and prompt-lepton background modelling systematics are the leading ones, however their impact is greater with respect to the Binary fit, contributing respectively at 6% and 4.6%.

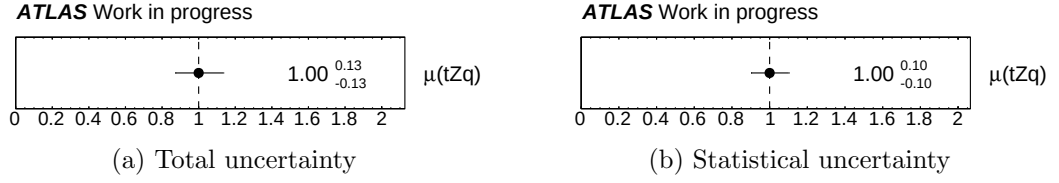


Figure 7.39: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Medium** selection using the MC-3 VV with Lorentz invariant variables NN.

tZq modelling systematics contributes for 2.2%, lower than MC statistics (2.5%).

The NP ranking (Figure 7.40) displays some variations with respect to the Binary (Figure 7.28). The two tZq uncertainties, A14 and showering, had a much lower impact in this fit, as they were ranked below the same four systematics regarding the leptons. Furthermore, luminosity and Pileup RW switched places, with their contributions still being around 1%. On the other hand, the leading systematics still remained the $t\bar{t}Z$ showering, as it has for all our fits, even if its impact increased from 3.8% to 4.3%. Similarly to the Binary fit, no pulls or correlations between systematics were found.

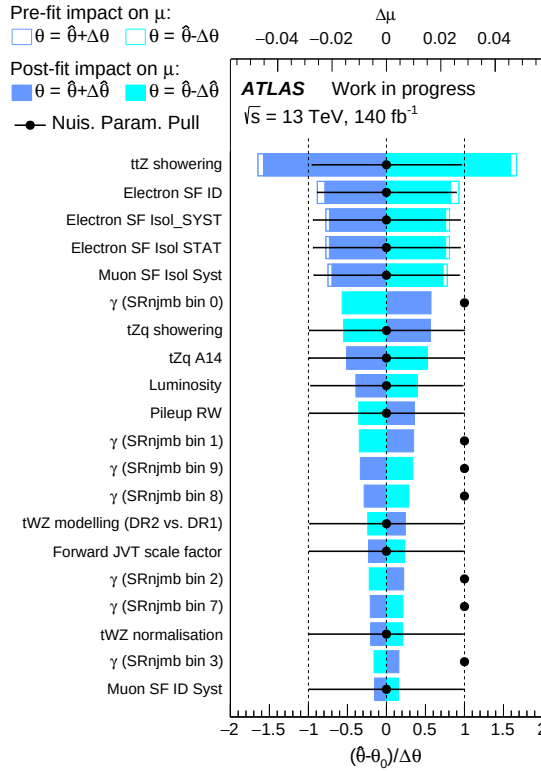


Figure 7.40: NP ranking for the fit with the **Medium** selection using the MC-3 VV with Lorentz invariant variables NN.

In summary, for this fit, in which it was not possible to use the cuts generated by the Multi Class, we used 1 SR with 10 bins. We defined 1 POI and 25 NPs, and the total uncertainty on the POI is +13%, -13%, Overall, this uncertainty is the worst among the

fits with the `Medium` selection, and it is also a bit worse than the Binary NN with the `Loose` selection.

Lorentz invariant variables: MC-3 $t\bar{t}Z$

Following down on the list of the trainings presented in Section 6.4.2, I will present a fit using the MC-3 NN trained with the Lorentz invariant variables with signal, $t\bar{t}Z$, and *Others* as targets, whose performance is presented in Section 6.4.2. Similarly to the MC-3 VV with Lorentz invariant variables, this NN does not allow for the definition of different regions. In particular, the signal response is so spread out that a SR definition would be impossible to define. Therefore, we used the same setup as we did for the MC-3 VV fit, and we used only one SR in which the tZq score was fitted. We do not expect much from this fit, as the training's performance was comparable with its counterpart with VV as a target, but I am still going to present it for completion.

The SR plot is presented in Figure 7.41. We observe the same situation mentioned for the VV training, in that in the last bin we have twice as much signal than backgrounds. Moreover, both Fakes and Diboson peak in the first bin, whereas the $t\bar{t}Z$ distribution is less flat than VV , as it starts decreasing around $O_{tZq} \simeq 0.3$.

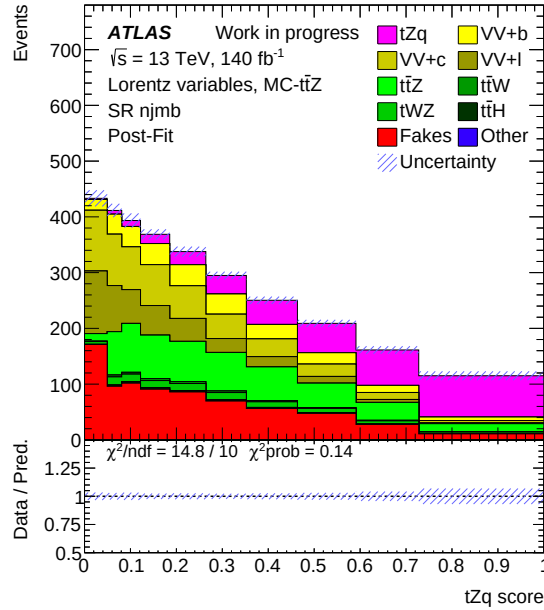


Figure 7.41: Post-fit SR plot displaying the tZq output distribution with the `Medium` selection using the MC-3 $t\bar{t}Z$ with Lorentz invariant variables NN.

Total and stat-only uncertainties are presented in Figure 7.42. The MLE for the POI is $\mu(tZq) = 1.00^{+0.13}_{-0.12} = 1.00 \pm 0.10(\text{stat})^{+0.08}_{-0.07}(\text{syst})$, which provides a small improvement with respect to the VV MC-3 fit. Moreover, the prompt-lepton background modelling contribution was halved, whereas the lepton's remained the same. Signal modelling impact

was reduced to 1.8%, while MC statistics rose to 2.8%.

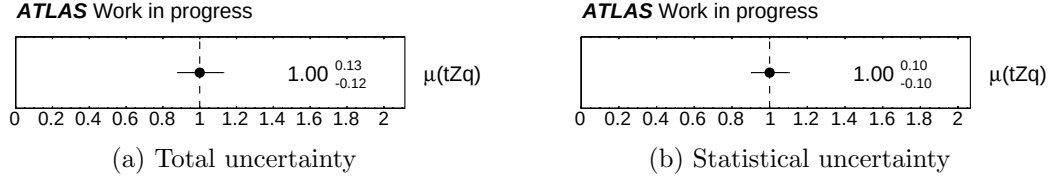


Figure 7.42: POI total uncertainty (left) and stat-only uncertainty (right) for the fit with the **Medium** selection using the MC-3 $t\bar{t}Z$ with Lorentz invariant variables NN.

The NP ranking (Figure 7.43) presents a very different scenario with respect to the other fit (Figure 7.40). For the first time, the $t\bar{t}Z$ showering is not the leading systematics, having been overcome by the ELECTRON SF ID uncertainty. Additionally, the tZq showering fell behind in the ranking, with an impact of less than 1%, whereas tZq A14 and luminosity's contributions remained the same.

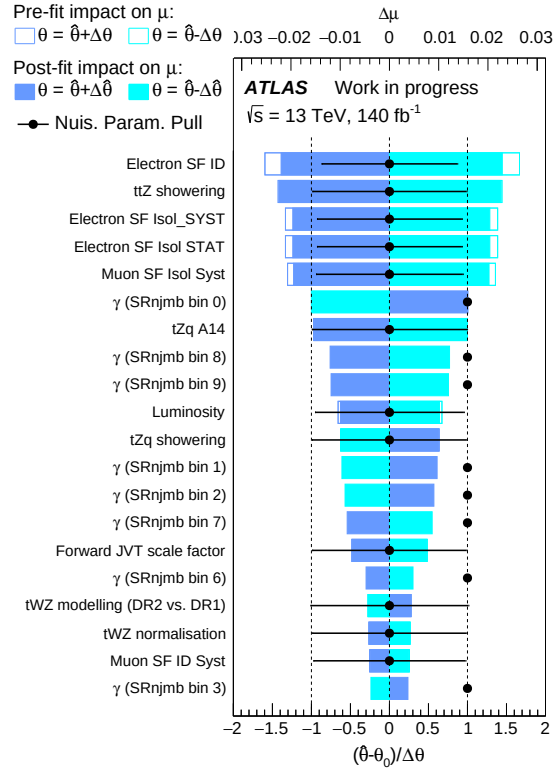


Figure 7.43: NP ranking for the fit with the **Medium** selection using the MC-3 $t\bar{t}Z$ with Lorentz invariant variables NN.

In brief, this fit used only 1 SR with 10 bins, 1 POI and 25 NPs. The uncertainty on the POI is +13%, -12%, thus resulting in this fit being better than the VV MC-3 with Lorentz invariant variables, but still worse than all the other fits performed using the Binary classifier.

These two fits with the Multi Class NNs will be compared with the next fits, in which

the standard variables were used to train the Multi Class NNs.

Standard variables: MC-3 VV

After seeing that the Lorentz invariant variables training's were not suitable for the fit, we moved onto fits in which the MC-3 NN was trained using the standard variables. For these fits, we expect to be able to create regions for the fit, because the NN performance showed significant improvements with respect to the Lorentz invariant one's. Similarly to what was done with the Lorentz invariant variables trainings', I will begin with the presentation of the Multi Class with VV as a target (labelled from here on as MC-VV), followed by the MC with $t\bar{t}Z$ and finally I will describe the fit using the mixed NN.

The MC-3 VV NN performance is presented in Section 6.4.2. Immediately we can see how this training allows us to generate regions enriched with a particular background, even if the $t\bar{t}Z$ response is not too well located because, as discussed in Section 6.4.2, the *Others* region is made of mostly Fakes. Nevertheless, we were able to define a tZq SR and two CRs, one enriched with VV and one with Fakes, $t\bar{t}Z$ and the others.

Once again, 3 orthogonal SRs were defined, as Table 7.5 displays. The signal region is the one which maximises the signal significance, having $S/\sqrt{S+B} = 9.66$ for $O_{VV} < 0.24$ and $O_{Others} < 0.29$. The Others-enriched region was defined as loose as possible, so that more $t\bar{t}Z$ could fit in that region. Therefore, all events with $O_{Others} > 0.29$ were included in the *Others* CR, whereas the remaining region, at high values of O_{VV} and low values of O_{Others} , was defined as the VV CR.

	SR tZq	CR VV	CR <i>Others</i>
Definition	$O_{VV} < 0.24$ $O_{Others} < 0.29$	$O_{VV} > 0.24$ $O_{Others} < 0.29$	- $O_{Others} > 0.29$
Jet regions	n_{jmb}	n_{jmb}	n_{jmb}
Number of bins	10	10	10
Variable fitted	O_{tZq}	O_{VV}	O_{Others}
Target contribution	51.1%	78.8%	75.5%
Signal contribution	51.1%	4.9%	5.8%

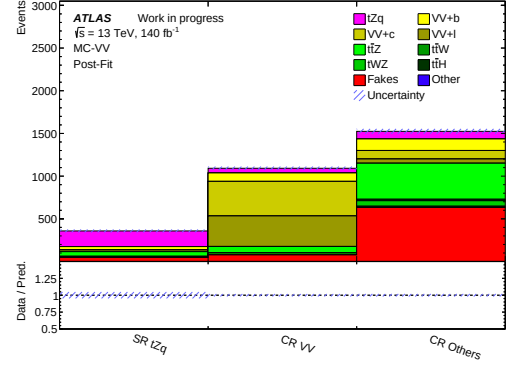
Table 7.5: SR definition for the MC-VV fit.

In Figure 7.44 the post-fit yields and the summary plot are presented. We can see how the regions are purer than they were for the Loose $t\bar{t}Z$ MC-3 fit (Table 7.3). More than half of the events in the SR are tZq , whereas in the other two regions the target contribution was more than 75%, whereas the signal contribution never exceeded 6%. Furthermore, more than 80% of the $t\bar{t}Z$ background were located in the *Others* CR, which was our biggest concern since its distribution in the 2D plot was not localised as well as other sources.

SR and CRs plots are represented in Figure 7.45. Once again, we can see the advan-

	SR tZq	CR VV	CR <i>Others</i>
tZq	183.1 ± 18.9	54.5 ± 5.9	88.7 ± 9.9
$VV + b$	34.8 ± 0.7	98.8 ± 2.1	135.2 ± 2.8
$VV + c$	20.1 ± 0.5	404.6 ± 8.2	99.6 ± 2.1
$VV + l$	4.7 ± 0.1	357.4 ± 7.5	49.7 ± 1.2
$t\bar{t}Z$	54.2 ± 7.2	72.6 ± 3.6	422.6 ± 14.5
$t\bar{t}W$	2.6 ± 0.1	2.9 ± 0.1	16.4 ± 0.4
tWZ	10.0 ± 1.2	21.9 ± 3.1	65.2 ± 10.2
$t\bar{t}H$	1.5 ± 0.0	1.7 ± 0.0	14.2 ± 0.3
Fakes	47.2 ± 1.1	77.6 ± 1.7	632.5 ± 16.9
Other	0.0 ± 0.0	0.0 ± 0.0	0.3 ± 0.0
Total	358.2 ± 16.9	1092.1 ± 19.6	1524.6 ± 29.0

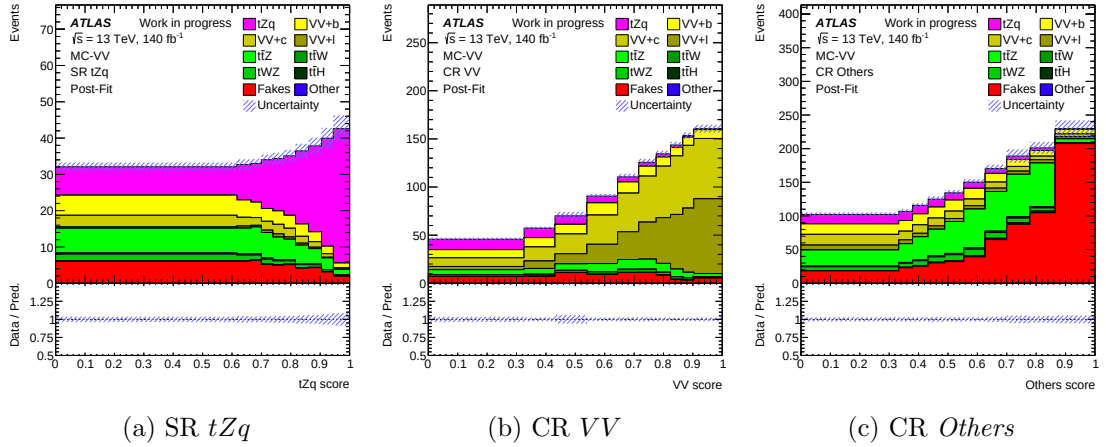
(a) Post-fit SR yields



(b) Summary plot with all regions

Figure 7.44: Post-fit SR yields (left) and summary plot with all regions (right) for the MC-VV fit.

tage of using a Multi Class instead of a Binary, displayed by the last bin of the distribution in the SR, in which the signal yields are 5 times more than the backgrounds'. Additionally, the VV CR has also sources correctly decreasing with the output, resulting in a final bin in which the Diboson contribution exceeds 95%, whereas the $t\bar{t}Z$ distribution in the *Others* CR is the only one which has not been treated correctly, as it peaks in the second to last bin and leaves the final bin with almost only Fakes. Nevertheless, these regions looks promising, as the fit showed.


 (a) SR tZq

 (b) CR VV

 (c) CR *Others*

Figure 7.45: Post-fit SR plots for the MC-VV fit.

As a matter of fact, this fit performed much better than the one with Lorentz invariant variables, as the uncertainties in Figure 7.46 show. The MLE for the POI is $\mu(tZq) = 1.00^{+0.12}_{-0.11} = 1.00 \pm 0.09(\text{stat}) \pm 0.07(\text{syst})$, which is the same result obtained with the Binary NN. Among the systematics, the leading contribution comes from the leptons, prompt-lepton background and signal modelling, with impacts of 4.5%, 3.8% and 2.7% respectively, comparable with their impact in the Binary fit (4.6%, 3.3% and 3.3%).

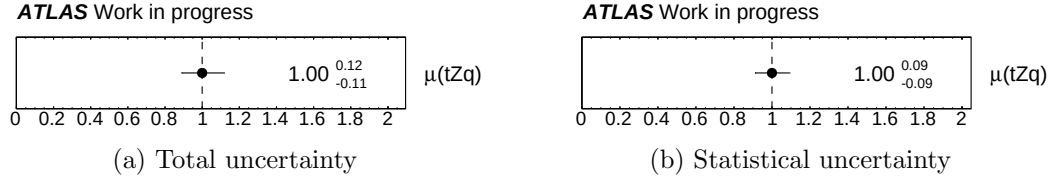


Figure 7.46: POI total uncertainty (left) and stat-only uncertainty (right) for the MC-VV fit.

Similarly to the Binary fit, the leading systematics are the $t\bar{t}Z$ showering and tZq A14, as displayed in the NP ranking in Figure 7.47. The tZq showering impact was reduced significantly, dropping below the 4 lepton systematics, whereas the other systematics' ranking remained the same. No significant pulls or correlations were present.

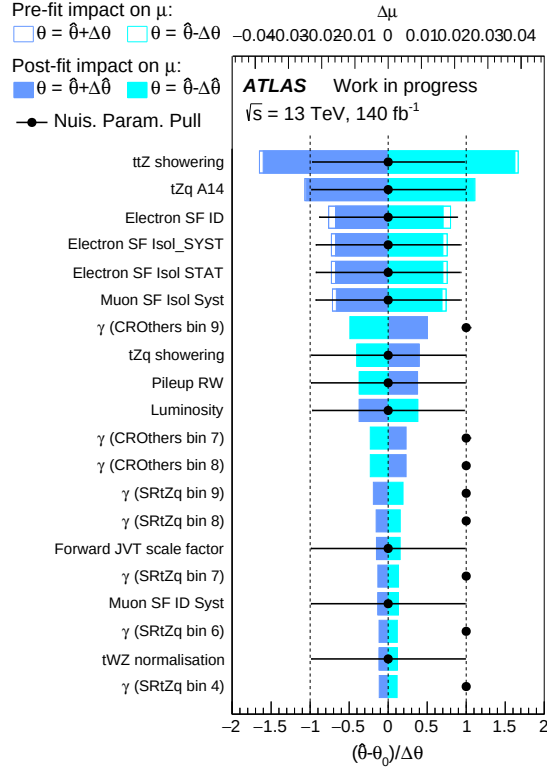


Figure 7.47: NP ranking for the MC-VV fit.

In summary, this fit used 3 regions with 10 bins each, 1 POI and 25 NPs. The total uncertainty on the POI is +12%, -11%. This uncertainty is lower than the one obtained with the Lorentz invariant variables, and it is of the same order as the one obtained with the Binary NN. However, it is still greater than both the Binary-SRs and Binary-3 fits.

Additionally, a fit on the tZq score was performed as well, in order to make a direct comparison with the Lorentz invariant variables fit. This fit will not be presented, and only the result is reported, which is $\mu(tZq) = 1.00^{+0.12}_{-0.11} = 1.00 \pm 0.09(\text{stat})^{+0.08}_{-0.07}(\text{syst})$. This result is significantly better than the other one, and it is only slightly worse than the

MC-VV fit, thus confirming that the standard variables perform better than the Lorentz invariant's.

Standard variables: MC-3 $t\bar{t}Z$

Having verified that the standard variables' fits perform better than their counterpart with the Lorentz invariant variables, all was left to decide whether the Multi Class with VV or with $t\bar{t}Z$ was the better one.

For this fit, the NN described in Section 6.4.2 was used. As the 2D plots show (Figure 6.40), this NN is better at generating regions to be used for the fit, because having $t\bar{t}Z$ as a target helps on locating him in the correct place, with Diboson and Fakes occupying the opposite corner. This situation did not occur when VV was used as a target because Diboson yields are lower than $t\bar{t}Z$, and therefore the *Others* classifier was not able to correctly act on $t\bar{t}Z$. Moreover, this NN had a higher maximum signal significance, which will result in an even purer SR.

A first attempt on the fit was performed applying the cuts in the usual way in order to maximise the signal significance in the SR, thus having a SR for $O_{t\bar{t}Z} < 0.39$ and $O_{Others} < 0.2$, a $t\bar{t}Z$ CR for $O_{t\bar{t}Z} > 0.39$ and a *Others* CR for $O_{t\bar{t}Z} < 0.39$ and $O_{Others} > 0.2$. The MLE for this fit is $\mu(tZq) = 1.00^{+0.12}_{-0.11} = 1.00 \pm 0.09(\text{stat})^{+0.07}_{-0.06}(\text{syst})$. I will not be showing this fit, but instead I will present an attempt made at improving this fit, since we observed that this fit performed better than all other Multi Class fits tested.

For all the fits shown so far, the regions were defined in the simplest way, meaning that the cuts were made with orthogonal lines at the values which maximised the signal significance. This time however, we tried to create the regions as pure as possible. In order to do so, I have selected the regions which optimised the cuts, and then I have calculated the analytical expression of the line which was then used to create the cuts. The outcome was the regions as in Figure 7.48, with the analytical expression of the line displayed in Equation (7.2.1).

$$O_{Others} = 1.158 \cdot O_{t\bar{t}Z} - 0.25 \quad (7.2.1)$$

With this new cuts, we get the regions defined in Table 7.6. With respect to other cuts, the $t\bar{t}Z$ CR is more pure, as its contribution rose from 48% to 53%. Therefore, we can expect to observe an improvement with these new cuts, since the $t\bar{t}Z$ showering uncertainty impact should decrease. Moreover, the tZq SR has a higher signal contribution than the one obtained in the MC-VV fit, as we predicted since this training had a higher maximum signal significance. The *Others* CR is purer as well, because it is made of Fakes and Diboson, though it is less pure than the one obtained in the Loose MC-3 fit.

The cuts are also displayed in Figure 7.48, where it is clear why the line in Equation (7.2.1) was chosen. From these cuts, we can expect the Fakes to be almost all located in the *Others* CR, as well as Diboson. The signal is well localised in the SR, whereas $t\bar{t}Z$ still has some small contributions outside its region. The Other category of sources, which refers to $t\bar{t}W$, $t\bar{t}H$ and 4tops, has not been correctly treated by the classifier, as they are

almost all located in the $t\bar{t}Z$ CR. However, this is not an issue as together they account for less than 2% of the total yields.

Yields and summary are presented in Figure 7.49. We can observe how the region definition worked almost perfectly for the Fakes, as only 13% of them it is not located in the *Others* CR, with 83% of Diboson located in that region, thus ensuring once more how this new cuts resulted in purer regions.

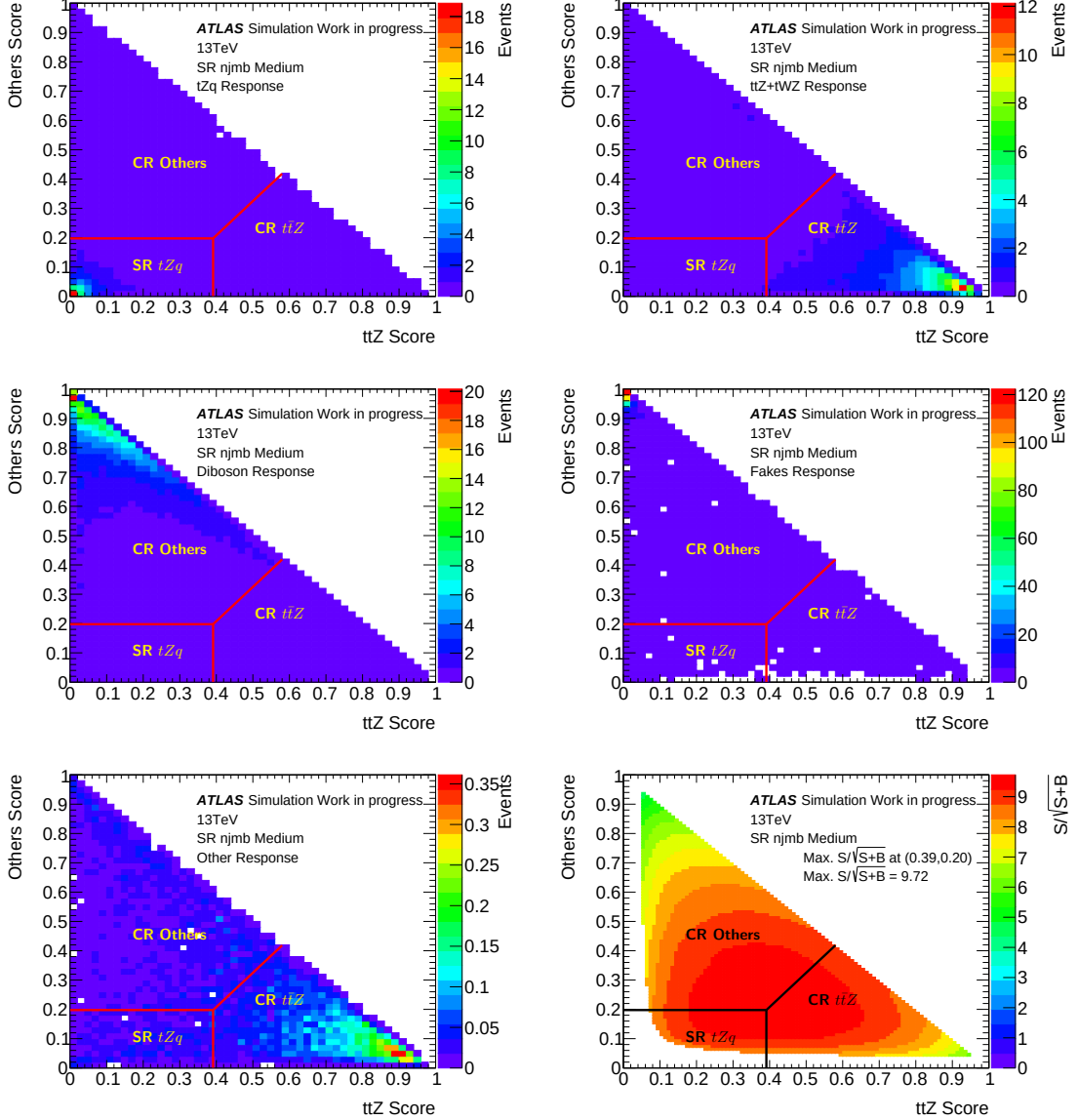


Figure 7.48: Regions definition in the 2D plot for the MC- $t\bar{t}Z$ fit.

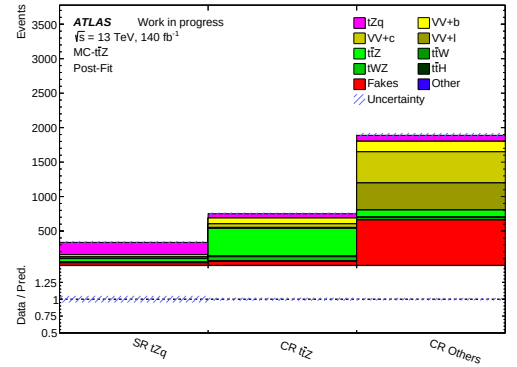
The post-fit plots for the three regions are presented in Figure 7.50. We can see how pure the regions are, as the SR has more than 85% tZq contribution in the last bin, with all the background's distributions decreasing, whereas the other two regions have the opposite

	SR tZq	CR $t\bar{t}Z$	CR $Others$
Definition	$O_{t\bar{t}Z} < 0.39$ $O_{Others} < 0.2$	$O_{t\bar{t}Z} > 0.39$ $O_{Others} < (7.2.1)$	$O_{t\bar{t}Z} < 0.39$ $O_{Others} > (7.2.1)$
Jet regions	n_{jmb}	n_{jmb}	n_{jmb}
Number of bins	10	10	10
Variable fitted	O_{tZq}	$O_{t\bar{t}Z}$	O_{Others}
Target contribution	53.5%	53.4%	90.1%
Signal contribution	53.5%	8.1%	4.5%

 Table 7.6: SR definition for the MC- $t\bar{t}Z$ fit.

	SR tZq	CR $t\bar{t}Z$	CR $Others$
tZq	178.5 ± 17.9	61.9 ± 7.0	85.9 ± 8.9
$VV + b$	31.0 ± 0.6	84.7 ± 1.8	153.1 ± 3.0
$VV + c$	20.6 ± 0.5	52.0 ± 1.1	451.6 ± 8.9
$VV + l$	5.7 ± 0.1	13.2 ± 0.3	392.9 ± 8.2
$t\bar{t}Z$	47.0 ± 6.5	401.3 ± 13.5	101.4 ± 4.9
$t\bar{t}W$	2.7 ± 0.1	11.1 ± 0.2	8.1 ± 0.2
tWZ	9.0 ± 1.2	57.7 ± 9.2	30.4 ± 3.9
$t\bar{t}H$	1.5 ± 0.0	11.6 ± 0.3	4.4 ± 0.1
$t\bar{t}$ & Z +jets	39.4 ± 0.9	57.3 ± 1.3	660.7 ± 16.7
Other	0.0 ± 0.0	0.3 ± 0.0	0.1 ± 0.0
Total	335.5 ± 16.5	751.1 ± 16.6	1888.6 ± 33.3

(a) Post-fit SR yields

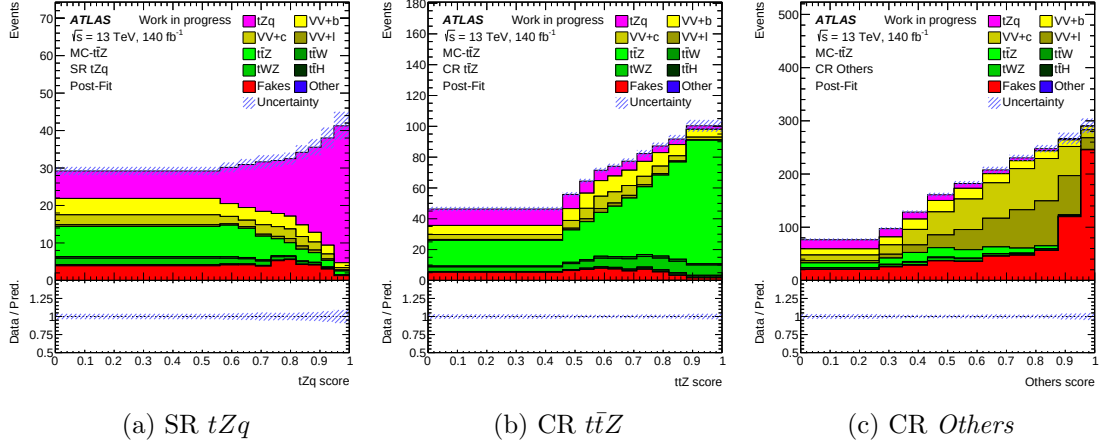


(b) Summary plot with all regions

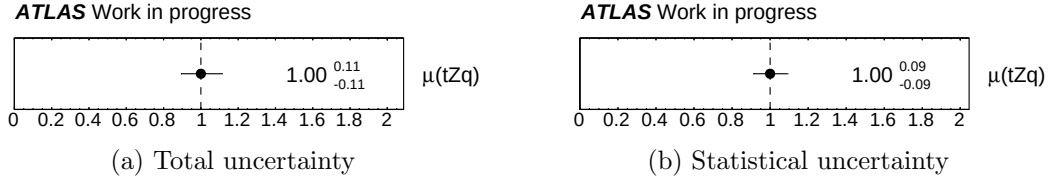
 Figure 7.49: Post-fit SR yields (left) and summary plot with all regions (right) for the MC- $t\bar{t}Z$ fit.

behaviour. The $t\bar{t}Z$ output works very well on signal and Fakes, leaving in the final bin almost only $t\bar{t}Z$ and some 20 Diboson events. As aforementioned, the idea behind this improved cuts was to optimise the $t\bar{t}Z$ CR, in order to reduce the $t\bar{t}Z$ showering impact, and this new region in which the $t\bar{t}Z$ contribution has been increased. Furthermore, the $Others$ output, which is the one with the highest separation, as Figure 6.39 tells us, is able to correctly treat all sources. The $t\bar{t}Z$ distribution, though very low in yields, has a small peak in the middle, before almost disappearing in the last bins. Similarly, the signal has almost no contribution for high values of the O_{Others} score, and it decreases throughout the distribution.

With these new cuts, we were able to reduce the total uncertainty, displayed alongside the stat-only uncertainty in Figure 7.51. The MLE for the POI is $\mu(tZq) = 1.00 \pm 0.11 = 1.00 \pm 0.09(\text{stat}) \pm 0.07^{+0.07}_{-0.06}(\text{syst})$, 1% lower in the upper total uncertainty than the one with looser cuts. Among the systematics, we have the greater contribution from the leptons (4.4%), prompt-lepton backgrounds (2.9%) and signal (2.5%) modellings. These impacts are almost equal to the ones obtained using the looser cuts, with however a small reduction in the showering impact, which contributed at 2.9%, and in the luminosity, whose


 Figure 7.50: Post-fit SR plots for the MC- $t\bar{t}Z$ fit.

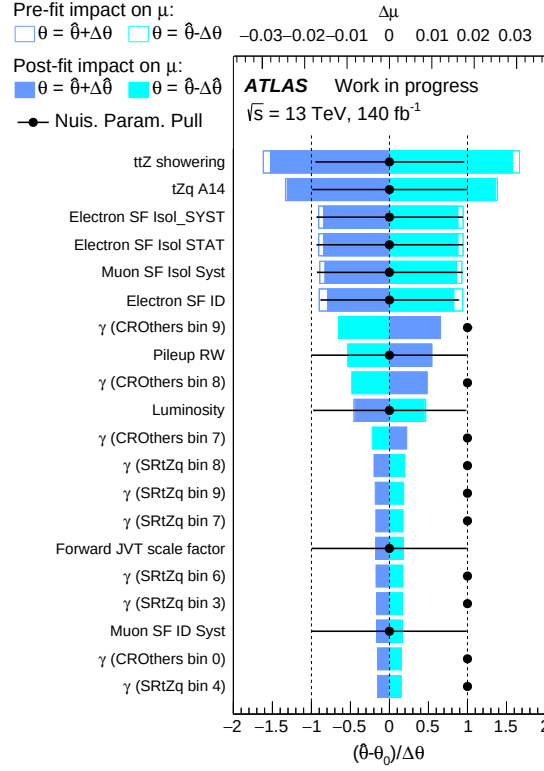
contribution was dropped from 1.1% to 0.8%. Additionally, the statistical uncertainty was a bit improved with this fit, going from 9.4% to 9.1% with tighter cuts.


 Figure 7.51: POI total uncertainty (left) and stat-only uncertainty (right) for the MC- $t\bar{t}Z$ fit.

The NP ranking, displayed in Figure 7.51, is identical to the one obtained with looser cuts, with the exception of a small reduction in the $t\bar{t}Z$ showering and in the luminosity contributions, though hard to spot from the plot, and in the tZq showering uncertainty, whose impact was reduced from 1% to less than 0.05%, thus resulting in this uncertainty not even being in the plot with the 20 highest NPs.

In summary, for this fit we defined 3 regions with 10 bins each, 1 POI and 25 NPs. The total uncertainty on the POI is +11%, -11%. This uncertainty is lower than what obtained with the MC-VV fit, as well as being lower than the result obtained for the fit with looser cuts. Moreover, to complete the comparison between this fit and the one with Lorentz invariant variables (Figure 7.42), we also tried to fit only one region to the tZq output. The MLE for this fit is $\mu(tZq) = 1.00^{+0.12}_{-0.11} = 1.00 \pm 0.09(\text{stat})^{+0.07}_{-0.06}(\text{syst})$, better than both the Lorentz invariant variables fit and the MC-VV fit, thus ensuring once more than the standard variables' trainings are more suited for the fit.

However, this fit also tells us another thing. We have seen that the fit using the MC-3 $t\bar{t}Z$ NN perform better than the ones using the MC-3 VV NN, even without applying more complex cuts. Therefore, the fit performed with the tighter cuts is the best fit we can perform with a Multi Class. This is due to the fact that the NN training was optimised,

Figure 7.52: NP ranking for the MC- $t\bar{t}Z$ fit.

and thus higher separations for the different outputs cannot be achieved, and by the fact that the cuts were optimised as well, leading to the purest regions which could have been defined. And this fit performed worse than the two Binary fits in which we used more than one region (**Binary-SRs** and **Binary-3**). Consequently, we came to the conclusion that the Binary NN is more suited for the fits, since the NN outputs are able to provide a higher separation than they are with the Multi Classes.

Mixed training

Nevertheless, we decided to test one final configuration for the Multi Class, which is the one labelled as **MC-mixed**. This fit uses the training described in Section 6.4.3, in which two different Multi Class NNs were trained, one with VV as a target for events with only 1 b -jet, whereas for events with 2 b -jets a $t\bar{t}Z$ MC-3 NN was implemented. As discussed in Section 6.4.3, this could deteriorate the training, but it can still bring improvements with the fit because the regions would be even purer, since Diboson and Fakes are mostly events with 1 b -jets, whereas $t\bar{t}Z$ makes up for more than 50% of the total events with 2 b -jets, as Table 6.8 displays.

As the 2D plots in Figures 6.43 and 6.46 presents, it is not so easy to define regions as it was for other multi classes. For the 1 b -region, the $t\bar{t}Z$ distribution is quite spread, as it happened for all MC-3 with VV , but that still is not too much of a problem. A cause

of concern is however the 2 b -jets region, in which Diboson is spread all over the plane. Nonetheless, Diboson's contribution in this region is only 14%, so the events that will end up in the $t\bar{t}Z$ CR will still be much less than the $t\bar{t}Z$ events.

Multiple attempts have been made for this fit, due to the fact that defining the regions is not as trivial as it was for other fits, and the best result was finally obtained by making loose cuts of 0.5 for all outputs. The regions definition is presented in Table 7.7. We can see how, in spite of the regions definition being loose, in that the cuts were made at greater values than the ones which optimise the signal significance, we are still left with pure regions. The SRs are the least pure out of all the regions, even if the percentage of signal located in that regions is around 80% for both. This is due to the fact that we are selecting the regions enriched with signals, but since the cuts are quite loose we are including a big amount of other sources, hence reducing the fraction of signal in the regions. On the other hand, the 4 CRs are more pure in their respective targets. For the 1 b regions we have more than 82% contribution from the target in both regions, with only 27% of Diboson and 42% of *Others* not being in their correct region. Similarly, 60% of all $t\bar{t}Z$ events with 2 b -jets are found in the $t\bar{t}Z$ 2 b CR, accounting for more than 80% of all events in that region, whereas the *Others* contribution in CR *Others* 2 b is 70%. Overall, we are left with regions enriched in a particular source, which can lead to significant improvements in the fit.

	Definition	Jets	Bins	Variable fitted	Target %	Signal %
SR tZq 1 b	$O_{VV}^{1b} < 0.5$ $O_{Others}^{1b} < 0.5$	$nj1b$	10	O_{tZq}^{1b}	29.4%	29.4%
CR VV 1 b	$O_{VV}^{1b} > 0.5$	$nj1b$	5	O_{VV}^{1b}	82.0%	2.7%
CR <i>Others</i> 1 b	$O_{Others}^{1b} > 0.5$	$nj1b$	5	O_{Others}^{1b}	84.5%	2.3%
SR tZq 2 b	$O_{t\bar{t}Z}^{2b} < 0.5$ $O_{Others}^{2b} < 0.5$	$nj2b$	10	O_{tZq}^{2b}	32.6%	32.6%
CR $t\bar{t}Z$ 2 b	$O_{t\bar{t}Z}^{2b} > 0.5$	$nj2b$	5	$O_{t\bar{t}Z}^{2b}$	81.3%	4.5%
CR <i>Others</i> 2 b	$O_{Others}^{2b} > 0.5$	$nj2b$	5	O_{Others}^{2b}	70.1%	6.3%

Table 7.7: Regions definition for the MC-mixed fit.

The summary plot is presented in Figure 7.53, whereas in Figure 7.54 all the regions plots are displayed. Having selected a looser cut on the tZq SRs, we have two signal regions with many background events, as Figures 7.54(a) and 7.54(d) represent. Nonetheless, in both regions there is good separation between the signal and the backgrounds, with the final bin having 80% of signal for both. On the other hand, we can see the advantage of using these 4 CRs in Figures 7.54(b), 7.54(c), 7.54(e) and 7.54(f). Not only we have regions with the biggest contribution coming from the target of the NN used for the fit in each region, but those NNs have all been trained correctly, with the targets increasing significantly in the highest bins, especially in the 1 b -regions. In detail, the VV 1 b CR

	SR tZq , 1b	CR VV , 1b	CR Others, 1b	SR tZq , 2b	CR $t\bar{t}Z$, 2b	CR Others, 2b
tZq	198.9 ± 19.9	28.4 ± 2.9	17.5 ± 2.0	65.5 ± 8.9	8.9 ± 1.0	7.1 ± 0.8
$VV + b$	94.6 ± 2.0	89.6 ± 2.0	45.1 ± 1.2	16.8 ± 0.3	10.2 ± 0.2	12.7 ± 0.4
$VV + c$	77.0 ± 1.8	391.5 ± 7.9	31.1 ± 0.9	6.1 ± 0.1	3.4 ± 0.1	15.2 ± 0.5
$VV + l$	28.6 ± 0.7	355.8 ± 7.4	20.2 ± 0.6	0.9 ± 0.0	0.4 ± 0.0	5.9 ± 0.3
$t\bar{t}Z$	111.8 ± 4.1	66.6 ± 3.9	100.4 ± 4.8	81.1 ± 7.9	163.4 ± 6.4	26.4 ± 1.0
$t\bar{t}W$	5.2 ± 0.1	2.6 ± 0.1	4.5 ± 0.1	4.0 ± 0.1	1.9 ± 0.0	3.8 ± 0.1
tWZ	29.0 ± 3.4	21.1 ± 3.0	20.5 ± 2.6	9.2 ± 1.9	12.9 ± 3.0	4.4 ± 1.0
$t\bar{t}H$	3.1 ± 0.1	1.6 ± 0.0	3.8 ± 0.1	3.0 ± 0.1	3.7 ± 0.1	2.2 ± 0.1
Fakes	128.9 ± 3.0	70.6 ± 1.7	503.9 ± 15.6	14.4 ± 0.4	5.2 ± 0.2	34.3 ± 1.5
Other	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0
Total	677.2 ± 19.4	1027.8 ± 19.2	747.0 ± 20.1	201.0 ± 9.3	210.1 ± 6.7	112.1 ± 3.4

Table 7.8: Post-fit yields in the 6 regions.

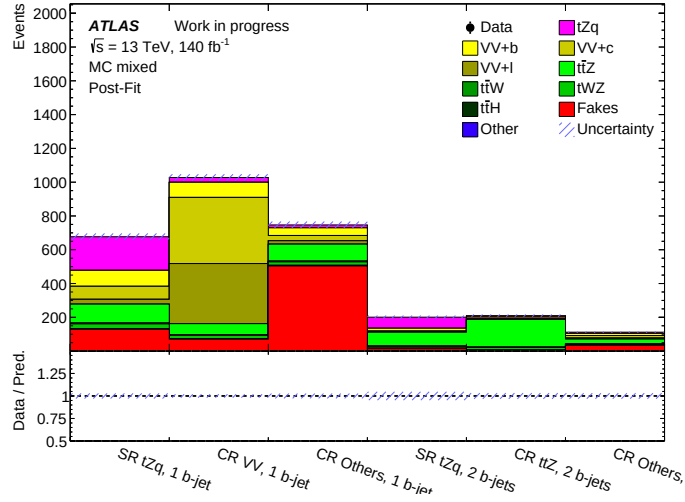


Figure 7.53: Summary plot with all the regions.

has a negligible contribution from sources different from VV in the last bin. Likewise, the last bin in the *Others 1b* region has more than 90% of Fakes, similarly to what happens in the $t\bar{t}Z$ 2 b CR, where the final bin has 56 events of which 48 are $t\bar{t}Z$. The only region in which we do not observe this situation is the *Others 2 b* CR. In this region the fit is made to the NN output with the lowest separation, as Figure 6.45 displays. Therefore, we could expect to observe this scenario. Nevertheless, the NN is still able to have the $t\bar{t}Z$ and tZq sources decreasing, with other sources increasing.

Unlike what we have observed with all other Multi Class fits, we have been able to match the uncertainty obtained using the Binary NN, especially for **Binary-SRs** and **Binary-3**, as displayed in Figure 7.55. The MLE for the POI is $\mu(tZq) = 1.00^{+0.11}_{-0.10} = 1.00 \pm 0.09(\text{stat}) \pm 0.06(\text{syst})$. Among the systematics, the three leading ones are once again the leptons (4.1%), the prompt-lepton background (2.8%) and signal (2.4%) modelling.

The NP ranking is displayed in Figure 7.56, and we can note how the systematics'

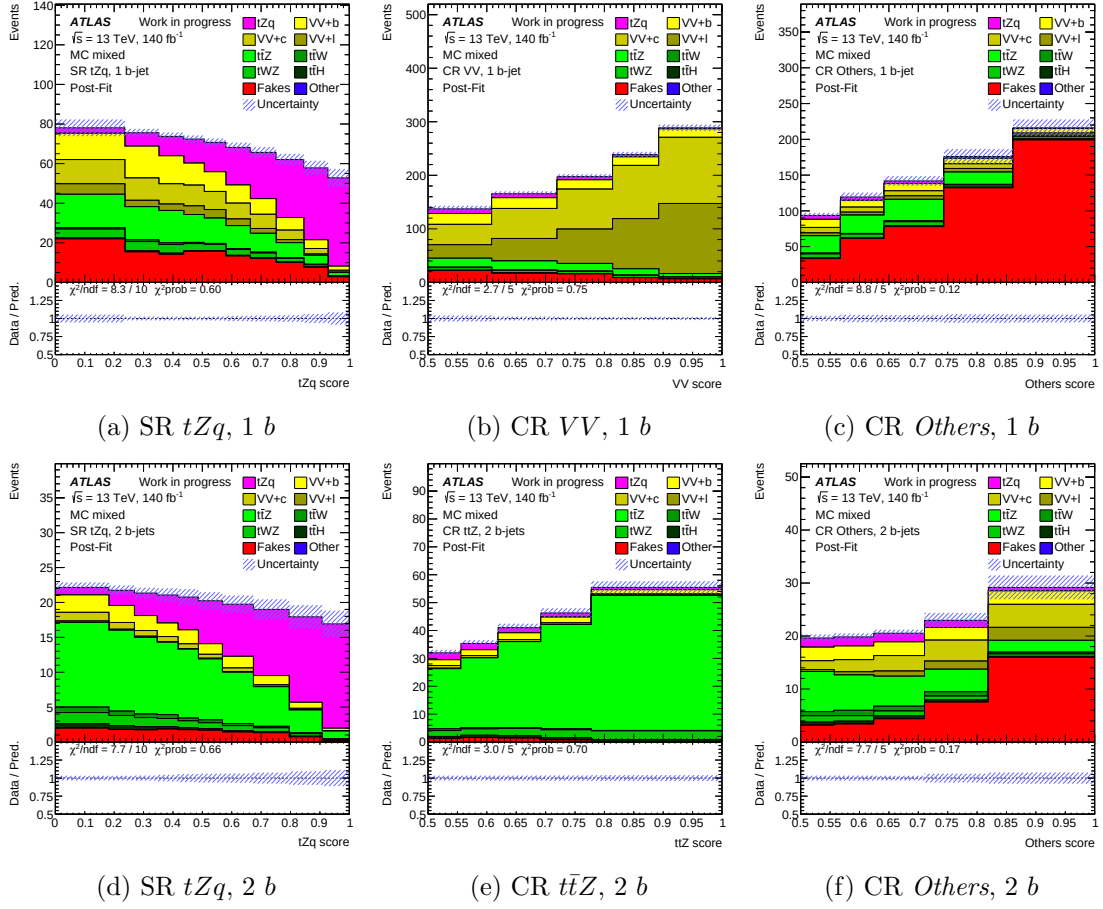


Figure 7.54: Post-fit SR plots for the MC-mixed fit.

ranking is the same as the ones for **Binary-SRs** (Figure 7.33) and **Binary-3** (Figure 7.37). The $t\bar{t}Z$ showering systematic uncertainty is still the leading one, followed by tZq A14 and then the four lepton systematics. The tZq showering, though small in impact, presents a constraint of 0.8, smaller than the 0.35 constraint obtained with the other two fits. The constraint is present because there is a splitting between different b -jet regions, but it is small because the split does not involve the total number of jets.

In summary, for this fit 6 regions were used, 2 SRs with 10 bins each and 4 CRs with 5 bins, for a total of 40 bins, with 1 POI and 25 NPs. The total uncertainty on the POI is +11%, -10%, resulting in this fit performing as good as the two best fits, **Binary-SRs** and **Binary-3**.

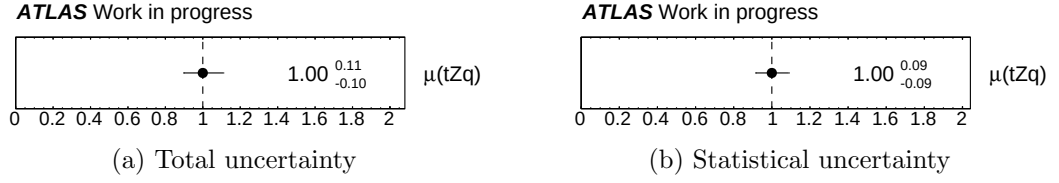


Figure 7.55: POI total uncertainty (left) and stat-only uncertainty (right) for the MC-mixed fit.

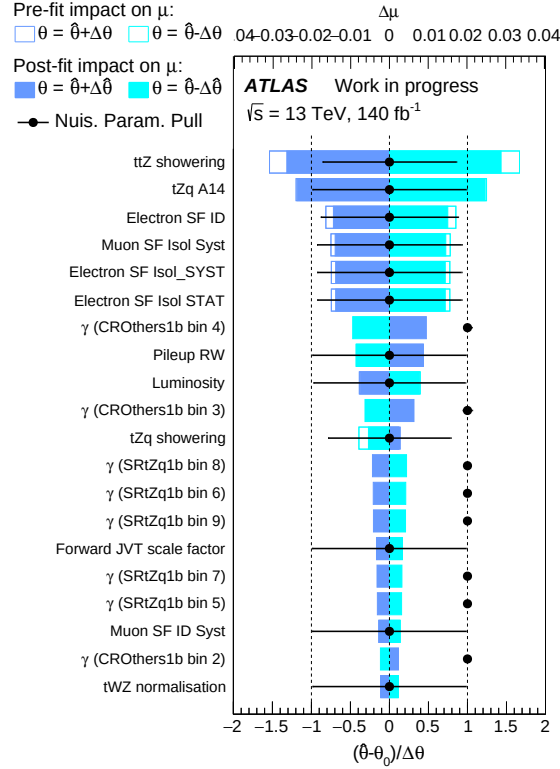


Figure 7.56: NP ranking for the MC-mixed fit.

Summary

In Table 7.9 a summary of all the fits performed is presented. As the table displays, for some fits we tested also a fit using the same setup, but splitting the regions based on the sign of the lepton coming from the W boson. As aforementioned, the charge of this lepton tells whether the tZq process occurs with a *top* or an *antitop* quark. The splitting, labelled as split $t/\bar{t}$, was implemented in order to see whether an improvement was obtained, also because this splitting caused the number of total bins to double. Nevertheless, no significant gain has been observed by splitting the *top* and *antitop* regions, with the only exception being the Binary with all regions together for the **Medium** selection.

Overall, we can see that the best 20 fits are all fits performed with the **Medium** selection and in which the NN was trained using the standard variables. Consequently, we can finally affirm that this selection is better than both **Loose** and **Default**, as well as

confirm that the standard variables are more suited than the Lorentz invariant variables.

An additional remark is that removing some events from the fit in order to generate purer regions ends up deteriorating the fit. This can be seen for instance in the “Binary RJ/no-RJ” fit, in which removing data in order to have a region with almost only signal (cutting on the NN output at 0.9 generates a region in which more than 90% of the events are tZq) gives a higher uncertainty. This is due to the fact that less statistics is used, thus increasing the relative statistical uncertainty.

Rank	Fit	$\sigma_{\mu}^{+}(\%)$	$\sigma_{\mu}^{-}(\%)$	Regions	Total bins	Selection
1	Binary_3	10.9	10.3	3	30	Medium
-1	MC_mixed	10.9	10.3	6	40	
-1	Binary_3, split $t/\bar{t}$	10.9	10.3	6	60	
4	Binary_SRs	11.0	10.4	7	70	
5	Binary RJ/no-RJ, split $t/\bar{t}$	11.3	10.7	4	40	
-5	MC $t\bar{t}Z$, improved cut	11.3	10.7	3	30	
-5	MC $t\bar{t}Z$, improved cut, split $t\bar{t}$	11.3	10.7	6	60	
8	Binary, split $t/\bar{t}$	11.4	10.7	2	20	
9	Binary RJ/no-RJ	11.4	10.8	2	20	
10	MC $t\bar{t}Z$	11.5	10.9	3	30	
11	Binary RJ/no-RJ, cut 0.5	11.6	10.9	2	20	
12	MC $t\bar{t}Z$, fit on tZq node	11.6	10.9	1	10	
13	Binary, all regions together	11.7	11.0	1	10	
14	MC VV	11.7	11.1	3	30	
15	MC $t\bar{t}Z$, combined score	11.8	11.1	1	10	
-15	Binary RJ/no-RJ, cut 0.7	11.8	11.1	2	20	
17	Binary RJ/no-RJ, cut 0.9	12.0	11.1	2	20	
18	MC VV , fit on tZq node	12.0	11.4	1	10	
19	Binary all regions, cut on 0.5	12.1	11.4	1	5	
20	MC 4 classes, combined	12.2	11.5	1	10	
21	MC $t\bar{t}Z$, fit on tZq node (Lor.)	12.8	12.2	1	10	Medium
22	Binary	12.8	11.8	1	10	Loose
23	MC VV , fit on tZq node (Lor.)	13.4	12.8	1	10	Medium
24	Binary RJ/no-RJ	13.4	12.5	2	20	Default
25	MC 4 classes, cuts	13.7	12.8	3	19	Default
26	MC 4 classes, combined score	13.7	13.0	1	10	Default
27	MC 4 classes, fit on tZq node	13.9	13.2	1	10	Default
28	MC $t\bar{t}Z$	16.7	15.1	3	30	Loose

Table 7.9: Summary of all fits performed.

In conclusion, we have three fits for which the overall uncertainty is +11%, −10%, which are **Binary-SRs**, **Binary-3** and **MC-mixed**. Therefore, for these three fits we also performed a fit using the full set of systematics, in order to be able to state which is the best setup for extracting the total uncertainty on the inclusive cross section.

7.3 Fit: complete set of systematics

In this section I will describe the fits performed using the complete set of systematics for the three best fits of the previous section.

For these fits, both the Diboson reweighting factors and the Fakes estimation described in Chapter 5 were implemented. Consequently, the Fakes sample was split based on the flavour of the fake lepton and on the fake lepton origin, same as described in Section 5.2. Additionally, the same four CRs used for the Fakes estimation were used, described in Table 5.3. The *Others* category now is made of not only the small contributions from 3 and 4 tops processes, but also tW , $t\bar{t}$ and Z +jets events in which all three leptons are prompt.

In addition to adding the full list of systematics as NPs, we also added 5 POIs. The idea behind adding POIs is to leave some backgrounds as free-floating, so that their normalisation will be evaluated from data. The 5 POI are the normalisation factors for $t\bar{t}Z$ and for the four Fakes components, meaning that for all the three main background sources (for Diboson the normalisation factors were extracted from data in Section 5.1), the normalisation is eventually extracted from data, once real data will be used also in the SRs. The normalisation factors are the same as the signal strength μ for the signal, meaning they are the ratio between the measured number of events and the expected from MC. Because these fits are Asimov, the normalisation factors for all backgrounds will be one, but, just like the signal, it is interesting to extract their uncertainty. Nevertheless, because the signal contribution in the Fakes CRs is negligible (less than 0.1%), real data will be displayed in the plots for those regions.

All systematics described in Section 7.1 were included, for a total of 186 NPs, grouped as described in Table 7.10. For the PDF uncertainties, all 101 eigenvectors were grouped into only 1 NP for each sample, labelled in the plots as PDF1. The luminosity uncertainty instead was not added to all free-floating processes, except for the signal, thus having an impact only on tZq , Diboson, tWZ , $t\bar{t}H$, $t\bar{t}W$ and Others.

To evaluate the grouped impact of the systematics, the systematics were grouped as follows. tZq systematics were divided in signal modelling, including scale variations (μ_R and μ_F), showering, and A14, and signal modelling PDF, which only has tZq PDF. Prompt-lepton background modelling includes $t\bar{t}Z$, VV , and tWZ systematics, whereas fake lepton backgrounds include all 12 $t\bar{t}$ uncertainties. Instrumental systematics instead were grouped in leptons (23), jets (48), b -tagging (85), PileUp modelling (1), and luminosity (1).

The fits were performed both with and without splitting the *top* and *antitop* quark contribution, meaning with or without splitting the events based on the charge of ℓ_W . Because the best fit setup was obtained with the splitting applied, I will be presenting only the three fits with the split.

In Table 7.11 the yields for the two different regions, *top* and *antitop*, are presented. As expected, the signal is asymmetric in favour of the *top* quark production. As described

Group	Sub-group	Nuisance Parameters
Theory (28)	tZq	4 (PDF, PS, A14, scale)
	$t\bar{t}Z$	4 (PDF, PS, A14, scale)
	tWZ	2 (Norm, DR1 vs DR2)
	VV	6 (PDF, scale; 2 for each flavour)
	$t\bar{t}$	12 (PS, Generator, hdamp; 3 for each flavour)
Instrumental (158)	Muons+Electrons	23
	JES	35
	JER	13
	b -tagging	85
	PileUp modelling	1
	Luminosity	1
-	-	Total = 186

Table 7.10: The complete list of systematics used for the final fits. PS refer to *parton shower*, scale refer to μ_R and μ_F variations, JES and JER are *Jet Energy Scale* and *Jet Energy Resolution*.

in Section 4.3.1, this is due to the single *top* quark in the tZq process being produced in the t -channel. Similarly, the ratio between the events in the two regions is 2 for $t\bar{t}W$, since the sign of the lepton coming from the W boson depends on the flavour of the initial state quark, as displayed in Figure 2.6. Furthermore, the Diboson+jets background is asymmetric as well, with a total ratio of 1.3 favouring the *top* quark production. The asymmetry comes from the WZ process, where the sign of the W boson, hence the sign of ℓ_W , depends on which valence quark has taken part in the interaction. On the other hand, all other backgrounds do not favour one process versus the other. For $t\bar{t}Z$, ℓ_W is the highest- p_T lepton whose invariant mass with the other two leptons differs the most from m_Z , and it can come from either the *top* or the *antitop* quark in the $t\bar{t}Z$ process. Therefore, because $t\bar{t}$ has no charge asymmetry, we expected to observe a ratio of 1. Likewise, $t\bar{t}H$ presents the same phenomena, because of its similarity to the $t\bar{t}Z$ process. Finally, the Fakes are also symmetric, because ℓ_W is usually a non-prompt lepton coming from a semileptonic decay of a B meson inside a b -jet, and it is therefore symmetric in its charge.

The overall ratio is 1.2, thus meaning that we expect the region with *top* quark processes to have more statistics than the one with *antitop* quark. Therefore, when measuring the production cross section of a *top* quark and an *antitop* quark, we expect the former to have a smaller uncertainty than the latter, due to its greater statistics.

In the following I will present the fits performed with this split implemented for the three best fits described in the previous section.

	$t, Q(\ell_W) = +1$		$\bar{t}, Q(\ell_W) = -1$		Ratio $t/\bar{t}$
tZq	207.9 ±	20.8	118.4 ±	11.8	1.8
$VV + b$	156.7 ±	3.2	112.2 ±	2.3	1.4
$VV + c$	279.3 ±	5.6	245.0 ±	5.2	1.1
$VV + l$	244.5 ±	5.4	167.3 ±	3.9	1.5
$t\bar{t}Z$	281.5 ±	10.8	268.1 ±	9.4	1.0
$t\bar{t}W$	14.3 ±	0.3	7.6 ±	0.2	2.0
tWZ	48.6 ±	7.4	48.5 ±	7.1	1.0
$t\bar{t}H$	8.8 ±	0.2	8.7 ±	0.2	1.0
Fakes	375.5 ±	10.2	381.8 ±	10.2	1.0
Other	0.2 ±	0.0	0.2 ±	0.0	1.0
Total	1617.4 ±	28.9	1357.8 ±	24.4	1.2

 Table 7.11: *Top* and *antitop* yields for the **Medium** selection.

7.3.1 Binary-SRs

For this fit, the same configuration as Section 7.2.3 was used, with the only difference being the splitting of the different jet multiplicity SRs based on the charge of ℓ_W , which generated a total of 14 SRs, alongside the 4 Fakes CRs. The post-fit yields are presented in Tables 7.12 and 7.13 for the 14 SRs and for the 4 Fakes CRs, respectively. Overall, we observe that the *top/antitop* ratios measured in Table 7.11 do not depend on the jet multiplicity, as they remain the same in all the different jet multiplicity regions.

Regarding the Fakes event, we can see that there are more muons (F-m-HF or F-Other) than electrons (F-e-HF or F-e-Other) in the SRs. This is not due to muons being more present than electrons in the process, but it is due to muons being easier to identify by the ATLAS detector. The signature of a muon is a track in the ID matched by a track in the Muon Spectrometer, which is easier to identify than an electron, whose signature is a track in the ID and a deposit in the ECal. Therefore, we observe more muons simply because they are easier to be seen by the detector. The opposite situation is observed in the Fakes CRs, for the same reason. Since it is harder to identify an electron, it is more likely that an electron is mistaken for a Fake, hence resulting in more electrons than muons in the Fakes CRs.

Furthermore, we can see that the HF components of the Fakes dominates the SRs, accounting for 85% of the total Fakes event.

The post-fit summary plot is presented in Figure 7.57. As aforementioned, we observe real data only in the 4 Fakes CRs, and we can see from the Data/Prediction section of the plot how the two HF regions, which are the two dominant, have a ratio Data/MC comparable to 1. On the other hand, the *Other* regions are overestimated in the MC, as their Data/MC ratio is smaller than 1. From this plot we can also observe the small difference between the *top* and the *antitop* regions, with the former having more events in all SRs. From the plot, it is clear how these events do not come from the Fakes, since in

	SR 2j1b, t	SR 3j1b, t	SR 4j1b, t	SR 5j1b, t	SR 3j2b, t	SR 4j2b, t	SR 5j2b, t
tZq	63.5 ± 8.8	55.7 ± 6.5	27.7 ± 4.1	8.7 ± 1.9	22.0 ± 2.8	20.9 ± 2.8	9.2 ± 1.6
$VV + b$	60.5 ± 9.7	39.3 ± 9.4	22.7 ± 6.1	9.8 ± 2.7	10.1 ± 2.5	7.7 ± 2.1	4.3 ± 1.2
$VV + c$	131.4 ± 17.3	79.1 ± 15.6	41.9 ± 9.1	17.6 ± 3.8	6.1 ± 1.2	4.4 ± 1.0	2.6 ± 0.6
$VV + l$	122.0 ± 15.8	71.4 ± 13.3	36.2 ± 7.8	15.5 ± 4.1	1.8 ± 0.5	1.6 ± 0.4	0.8 ± 0.2
$t\bar{t}Z$	20.2 ± 2.9	42.7 ± 5.2	46.4 ± 5.4	32.7 ± 4.3	37.3 ± 4.8	55.5 ± 6.0	45.7 ± 4.6
$t\bar{t}W$	0.5 ± 0.0	0.3 ± 0.0	0.1 ± 0.0	0.0 ± 0.0	0.4 ± 0.0	0.2 ± 0.0	0.2 ± 0.0
tWZ	8.1 ± 1.0	12.3 ± 1.5	9.7 ± 1.6	5.1 ± 0.9	4.0 ± 0.6	5.3 ± 1.4	3.9 ± 1.2
$t\bar{t}H$	0.8 ± 0.1	1.3 ± 0.1	1.2 ± 0.1	0.9 ± 0.1	1.4 ± 0.1	1.7 ± 0.1	1.3 ± 0.1
Other	6.3 ± 2.4	1.4 ± 0.5	0.6 ± 0.2	0.3 ± 0.1	1.0 ± 0.1	0.5 ± 0.1	0.2 ± 0.1
F-e-HF	58.0 ± 17.2	25.1 ± 11.1	12.1 ± 4.4	3.7 ± 1.5	2.5 ± 1.6	3.4 ± 1.9	1.0 ± 0.5
F-e-Other	11.7 ± 4.9	14.3 ± 4.3	3.9 ± 1.9	1.4 ± 0.4	3.1 ± 2.9	2.1 ± 2.2	1.2 ± 1.2
F-m-HF	102.9 ± 24.1	52.6 ± 15.5	20.8 ± 5.9	8.4 ± 3.2	6.4 ± 2.2	3.7 ± 1.3	1.4 ± 0.7
F-Other	23.2 ± 8.5	4.2 ± 2.4	3.6 ± 1.6	1.6 ± 0.6	3.9 ± 1.6	2.7 ± 1.2	1.3 ± 0.6
Total	609.2 ± 18.4	399.8 ± 13.1	226.9 ± 8.5	105.8 ± 5.6	100.1 ± 5.1	109.5 ± 5.1	73.2 ± 3.9

	SR 2j1b, $\bar{t}$	SR 3j1b, $\bar{t}$	SR 4j1b, $\bar{t}$	SR 5j1b, $\bar{t}$	SR 3j2b, $\bar{t}$	SR 4j2b, $\bar{t}$	SR 5j2b, $\bar{t}$
tZq	37.4 ± 5.0	31.7 ± 3.7	15.0 ± 2.2	4.7 ± 1.1	13.1 ± 1.6	11.3 ± 1.6	5.1 ± 1.0
$VV + b$	42.7 ± 6.8	28.5 ± 6.8	15.8 ± 4.3	6.8 ± 1.9	6.7 ± 1.7	5.2 ± 1.4	2.8 ± 0.8
$VV + c$	121.8 ± 16.4	68.9 ± 13.0	34.5 ± 7.4	13.8 ± 3.1	4.8 ± 1.0	3.4 ± 0.8	1.9 ± 0.4
$VV + l$	85.6 ± 11.3	48.7 ± 9.3	24.0 ± 5.1	9.8 ± 2.2	1.2 ± 0.3	1.0 ± 0.3	0.5 ± 0.2
$t\bar{t}Z$	19.2 ± 2.6	41.3 ± 5.5	44.2 ± 5.3	30.7 ± 3.8	35.7 ± 4.3	53.3 ± 5.5	42.8 ± 4.3
$t\bar{t}W$	0.3 ± 0.0	0.2 ± 0.0	0.1 ± 0.0	0.0 ± 0.0	0.2 ± 0.0	0.1 ± 0.0	0.1 ± 0.0
tWZ	8.1 ± 0.9	12.3 ± 1.7	9.6 ± 1.4	5.2 ± 0.9	4.0 ± 0.7	5.2 ± 1.1	4.0 ± 1.2
$t\bar{t}H$	0.8 ± 0.1	1.3 ± 0.1	1.3 ± 0.1	0.9 ± 0.0	1.3 ± 0.1	1.6 ± 0.1	1.4 ± 0.1
Other	0.5 ± 1.0	2.6 ± 1.1	0.7 ± 0.2	0.4 ± 0.1	0.6 ± 0.2	0.4 ± 0.1	0.4 ± 0.2
F-e-HF	62.3 ± 17.6	31.2 ± 10.2	11.7 ± 5.3	5.6 ± 1.6	3.6 ± 1.4	2.2 ± 1.0	0.7 ± 0.4
F-e-Other	11.4 ± 4.8	11.1 ± 3.8	2.7 ± 1.9	2.8 ± 2.7	2.6 ± 2.5	1.5 ± 1.8	0.9 ± 0.9
F-m-HF	120.3 ± 23.9	55.2 ± 13.2	19.8 ± 6.7	8.0 ± 2.6	6.7 ± 3.0	4.3 ± 1.6	1.2 ± 0.8
F-Other	9.4 ± 5.1	3.6 ± 1.8	2.3 ± 1.1	1.8 ± 0.7	2.5 ± 1.2	1.7 ± 1.1	0.8 ± 0.7
Total	519.6 ± 16.5	336.5 ± 10.5	181.8 ± 7.1	90.4 ± 4.9	83.0 ± 4.4	91.2 ± 4.6	62.5 ± 3.7

Table 7.12: Post-fit SR yields for the Binary-SRs fit. Top row is *top*, bottom row is *antitop*.

some regions they even prefer the *antitop* over the *top*, but instead come from Diboson and the signal, as expected. SRs plots are presented in Figure 7.58. It is interesting to note how both *top* and *antitop* regions follow almost the same distribution, due to them being trained together. Nevertheless, there are some differences, especially for the Fakes, which might be caused by the fact that the charge of ℓ_W is used as one of the input variables for the training, and its impact is also high, as it is the third highest ranked variable in the training, as displayed by Figure 6.23.

Stat-only and total uncertainties are presented in Figure 7.59. We can immediately note how the statistical uncertainty for the signal is the biggest one, since it is the process with the lower statistics. On the other hand, the statistical uncertainty for the HF Fakes is around 2%, because the number of Fake events is much greater. The MLE for the signal POI is $\mu(tZq) = 1.00^{+0.13}_{-0.12} = 1.00^{+0.10}_{-0.09}(\text{stat})^{+0.09}_{-0.08}(\text{syst})$. The systematics impact is dominated by the theoretical uncertainties (6.8%), with the instrumental systematics contributing for 4.5%. Among all systematics, the greatest impact is given by the signal modelling (4.7%), particularly by the scale uncertainties μ_R and μ_F , with an impact of 4.3%. The latter was expected, since, as explained in Section 7.1.2, the MC process is generated in 4FS, and therefore the Born cross section already has a $\alpha_s(\mu_R^2)$ dependence,

	CRFakesElHF		CRFakesElOther		CRFakesMuHF		CRFakesOther	
tZq	18.1 ±	2.5	2.1 ±	0.3	12.3 ±	1.5	0.9 ±	0.1
$VV + b$	23.3 ±	5.4	3.0 ±	0.6	15.5 ±	3.4	1.1 ±	0.3
$VV + c$	42.7 ±	7.4	29.8 ±	4.9	30.7 ±	5.3	13.1 ±	2.3
$VV + l$	32.4 ±	5.4	214.6 ±	34.1	23.9 ±	4.2	87.5 ±	13.2
$t\bar{t}Z$	54.7 ±	7.5	2.6 ±	0.4	35.0 ±	4.1	1.0 ±	0.2
$t\bar{t}W$	5.2 ±	0.3	0.0 ±	0.0	0.0 ±	0.0	0.0 ±	0.0
tWZ	4.2 ±	0.6	0.8 ±	0.1	2.4 ±	0.5	0.4 ±	0.1
$t\bar{t}H$	25.2 ±	1.0	0.1 ±	0.0	12.4 ±	0.4	0.0 ±	0.0
Other	338.7 ±	49.3	180.6 ±	57.9	85.0 ±	11.4	13.6 ±	6.5
F-e-HF	10 056.1 ±	703.3	3165.9 ±	379.0	24.9 ±	4.4	6.5 ±	2.7
F-e-Other	2211.2 ±	679.0	6038.9 ±	400.7	19.1 ±	12.2	15.7 ±	10.4
F-m-HF	84.7 ±	13.1	50.7 ±	13.7	6865.2 ±	152.5	3173.1 ±	297.0
F-Other	59.5 ±	18.5	44.8 ±	15.1	445.5 ±	134.0	1241.5 ±	308.8
Total	12 956.2 ±	129.2	9733.8 ±	101.4	7571.9 ±	88.8	4554.6 ±	66.7

Table 7.13: Post-fit Fakes CR yields.

due to the QCD $g \rightarrow b\bar{b}$ vertex. This systematic includes also the variation of μ_F , but its impact is less than μ_R . All PDF uncertainties account for 0.7%, with the tZq PDF systematics accounting alone for 0.5%. It is also interesting to note that the leptons uncertainties are significantly reduced with respect to the previous fit, due to the work done on estimating the Fakes, accounting for 2.7%. Fake lepton backgrounds' impact is 4.4%, greater than the prompt-lepton background, at 2.8%. All b -tagging uncertainties account for 1.5%, MC statistics for 1.6%, and luminosity for 0.7%.

The NP ranking for all six POIs is presented in Figure 7.61. For the signal POI (Figure 7.61(a)) we can observe what stated above. The highest contribution comes from the scale variation for tZq , followed by the tZq A14 and the showering uncertainties. With respect to the same fit with the small set of systematics, the tZq showering impact was increased, being now ranked higher than the $t\bar{t}Z$ showering. Similarly to what observed in Figure 7.33, there is a 0.25 constraint for the tZq showering, given by the splitting between different jet multiplicity regions, and a similar constraint is seen also for the $t\bar{t}$ generator for the Muon HF component of the Fakes.

On the other hand, the $t\bar{t}Z$ showering is the systematics which impacts the most the POI for the $t\bar{t}Z$ background. The scale variation for $t\bar{t}Z$ has a greater impact than it had on the tZq POI, but it still remains out of the highest 10 ranked variables, with the μ_R and μ_F variation for $VV + b$ being the one with the greater impact among the five scale variations, which together have an impact of 2.9%. The tZq showering uncertainty contribution is much reduced, whereas some $t\bar{t}$ generator and showering systematics remain among the most significant variables. Finally, for the first time we observe the tWZ modelling systematic uncertainty that high in a NP ranking. This is due to that systematic referring to the DR1 vs DR2 diagram removal scheme, which accounts for the interference between

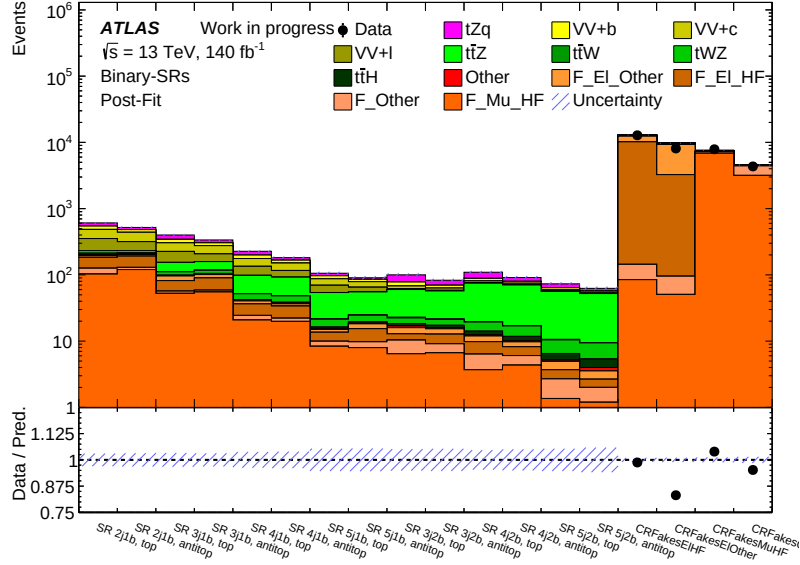


Figure 7.57: Post-fit summary plot displaying the yields in all the regions for the Binary-SRs fit.

$t\bar{t}Z$ and tWZ , and thus having an impact on the $t\bar{t}Z$ normalisation factor.

Finally, the four Fakes POIs all present a similar ranking. The $t\bar{t}$ showering, generator and h_{damp} uncertainties are the ones with the greatest impact in all the regions. In detail, there is always a significant contribution from $t\bar{t}$ generator MuHF, which also reports a constraint of 0.4. Other significant contributions come from other lepton uncertainties, such as ELECTRON SF ID and ELECTRON SF RECO, especially in the first three regions, whereas jet uncertainties have a great impact on $N_{\text{FakesOther}}$.

In Figure 7.60 the pull plot for the theoretical systematics is presented, and the constraints on the tZq showering, as expected because of the splitting between different jet multiplicity regions, and on the $t\bar{t}$ generator MuHF can be clearly seen. Furthermore, smaller constraints are also present for other systematics regarding $t\bar{t}$, such as $t\bar{t}$ generator ElHF and $t\bar{t}$ shower MuHF. No instrumental systematics constraint was observed, therefore the pull plot will not be shown. Overall, the only significant anti-correlations are observed between the $t\bar{t}$ systematics, with the highest one being a -52.7% anti-correlation between $t\bar{t}$ generator ElOther and $t\bar{t}$ generator ElHF.

In summary, for this fit a total of 186 NPs were considered, alongside 6 POIs. A total of 14 SRs were used, with 10 bins each, and 4 CRs, for a total of 180 bins. The total uncertainty on the inclusive cross section is +13%, -12%. With respect to the small set of systematics, the uncertainty was increased by 2 percentage points, being +11%, -10%. Nevertheless, we were able to reduce the total uncertainty with respect to the previous analysis by 16%, going from 15% to 12.5%.

The total uncertainty on the $t\bar{t}Z$ normalisation factor is slightly reduced (+11.6%, -11.1%) with respect to the signal cross section. For the Fakes instead we have the two HF

7.3. FIT: COMPLETE SET OF SYSTEMATICS

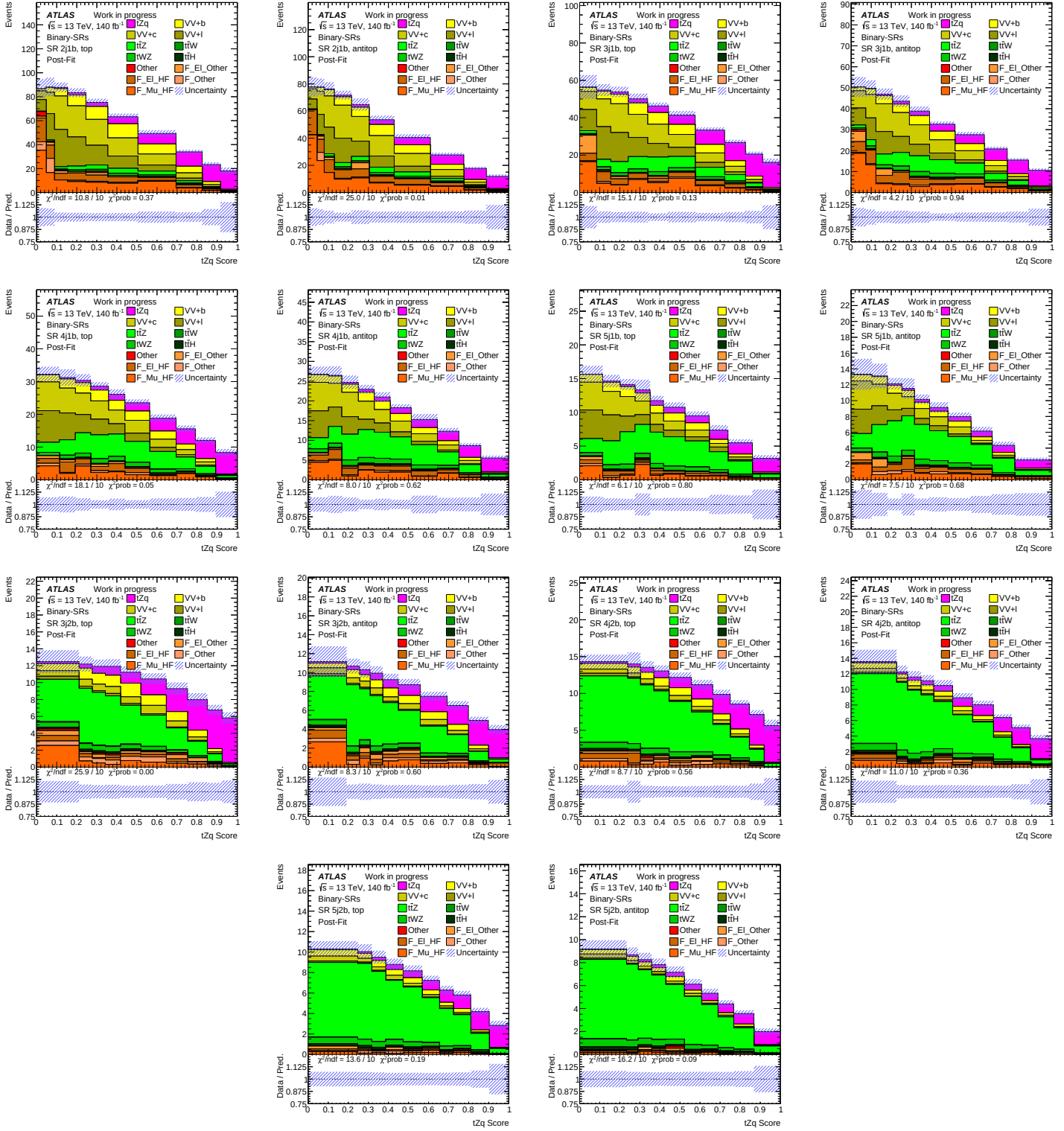


Figure 7.58: Post-fit SRs plots for the Binary-SRs fit.

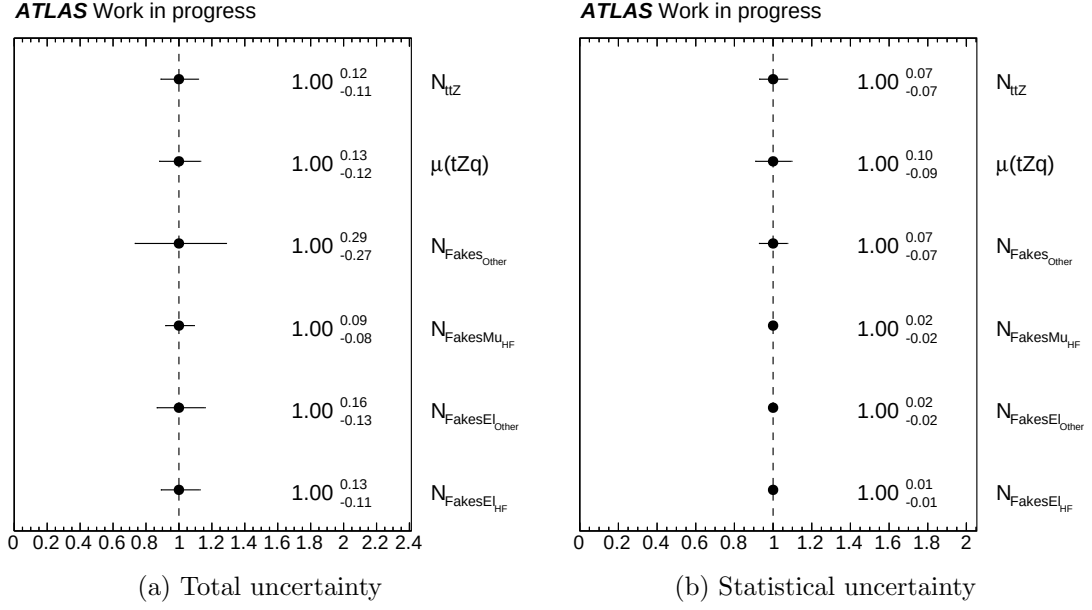


Figure 7.59: POI total uncertainty (left) and stat-only uncertainty (right) for all the POIs in the Binary-SRs fit.

components with small uncertainties (8.5% for Muons and 12.5% for Electrons), whereas the OTHER NFs have greater uncertainties, 14.5% for Electrons and 28% for the last one. The last two uncertainties are significantly lower than the ones obtained with the fit to data (Figure 5.9), in which the total uncertainties on $N_{FakesOther}$ and $N_{FakesEl_{Other}}$ was more than 50% and 27%, respectively.

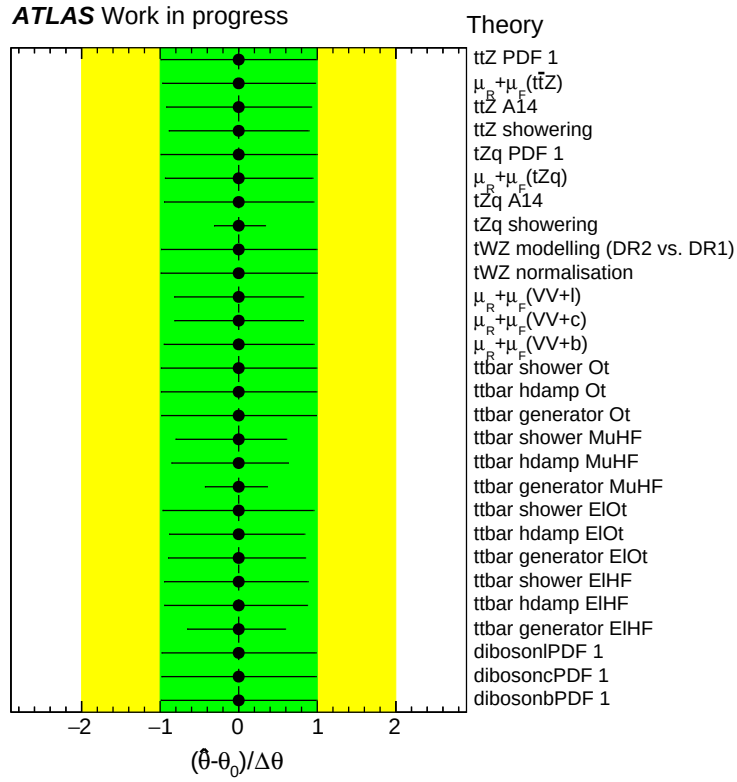


Figure 7.60: Pull plot for the theoretical systematics in the Binary-SRs fit.

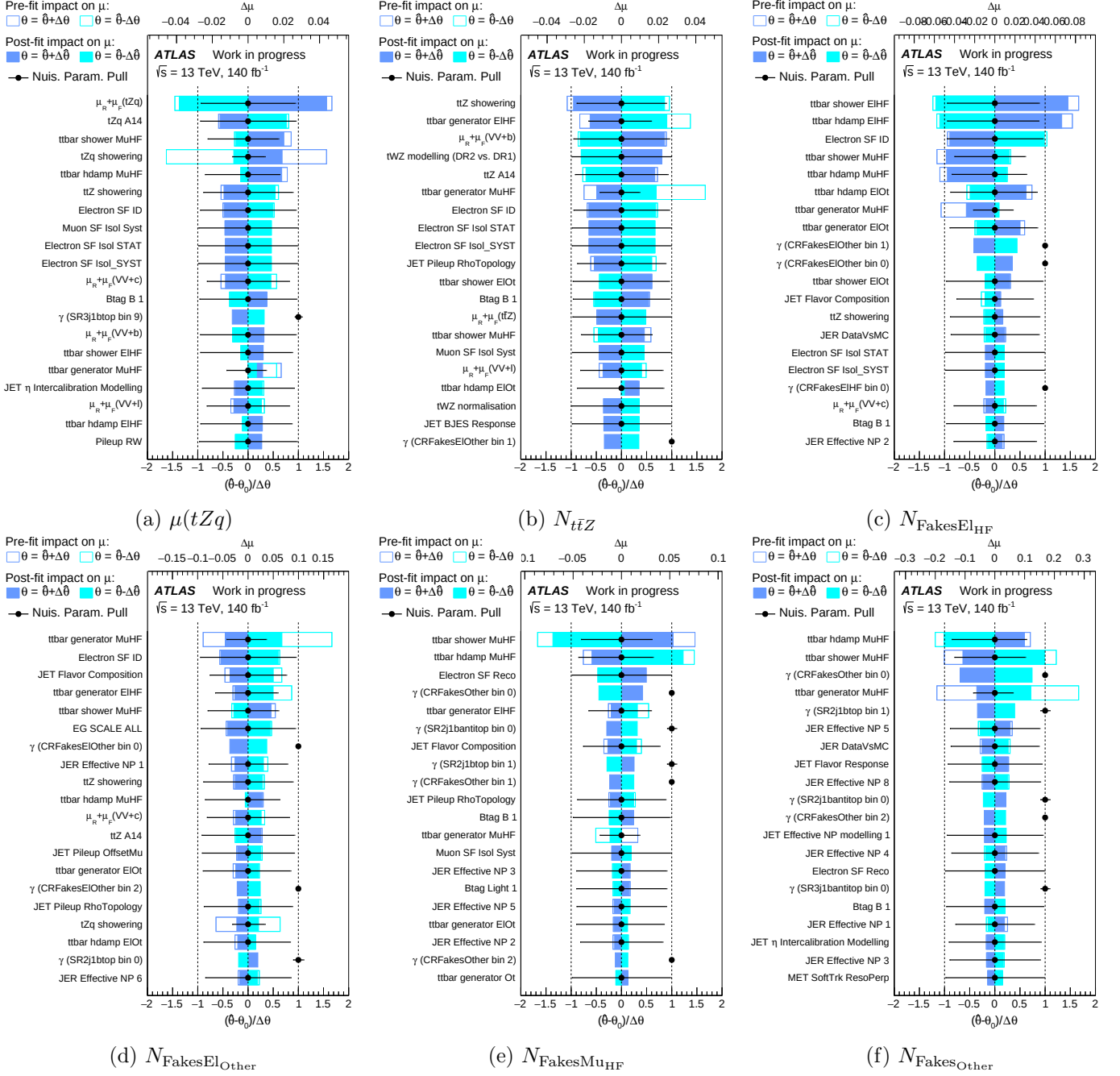


Figure 7.61: NP ranking for the six POIs in the Binary-SRs fit.

7.3.2 Binary-3

Following up on the fits with the full set of systematics, I will present the full fit using the **Binary-3** fit setup, described in Section 7.2.3. Once again, the three SRs (**no-RJ**, **RJ+1b**, and **RJ+2b**) defined in Table 7.4 in order to group similar jet regions together, were split based on the charge of ℓ_W , thus generating 6 SRs, which are accompanied by the usual 4 CRs for the Fakes estimation.

In Tables 7.14 and 7.15 the SRs and CRs post-fit yields are presented. Since the regions for this fit are generated by grouping together regions from the previous fit, we observe the same ratio between the *top* and the *antitop* region as Table 7.11. The yields in the Fakes CRs are the same as the ones in Table 7.13, with the only difference being the uncertainty, which in this case is lower in all regions. Regarding the SRs, we can see that the splitting helped us generating a purer $t\bar{t}Z$ region. This is due to $t\bar{t}Z$ being symmetric with respect to the the charge of ℓ_W , whereas the signal is not. Therefore, since this region is dominated by $t\bar{t}Z$, we are left with 63% $t\bar{t}Z$ in the region, whereas in the **RJ+2b** region without the splitting (Figure 7.34) the $t\bar{t}Z$ contribution was of 54%.

	SR no-RJ, t	SR no-RJ, $\bar{t}$	SR RJ+1b, t	SR RJ+1b, $\bar{t}$	SR RJ+2b, t	SR RJ+2b, $\bar{t}$
tZq	85.5 ± 10.6	50.5 ± 6.0	92.1 ± 11.5	51.4 ± 6.5	30.1 ± 4.3	16.3 ± 2.5
$VV + b$	70.6 ± 11.7	49.4 ± 8.1	71.8 ± 17.5	51.1 ± 12.4	12.0 ± 3.1	8.1 ± 2.1
$VV + c$	137.5 ± 17.7	126.6 ± 16.7	138.6 ± 27.4	117.2 ± 22.5	7.0 ± 1.5	5.3 ± 1.1
$VV + l$	123.8 ± 16.3	86.8 ± 11.7	123.2 ± 25.2	82.5 ± 16.7	2.3 ± 0.6	1.5 ± 0.4
$t\bar{t}Z$	57.5 ± 8.1	54.9 ± 7.5	121.7 ± 14.6	116.2 ± 14.8	101.2 ± 10.7	96.0 ± 10.2
$t\bar{t}W$	0.9 ± 0.1	0.5 ± 0.0	0.5 ± 0.1	0.3 ± 0.0	0.3 ± 0.0	0.2 ± 0.0
tWZ	12.1 ± 1.6	12.0 ± 1.5	27.1 ± 3.9	27.1 ± 3.9	9.2 ± 2.6	9.2 ± 2.3
$t\bar{t}H$	2.2 ± 0.1	2.1 ± 0.1	3.4 ± 0.1	3.4 ± 0.1	3.0 ± 0.1	3.0 ± 0.1
Other	7.3 ± 1.5	1.2 ± 1.4	2.4 ± 0.7	3.6 ± 1.2	0.7 ± 0.1	0.8 ± 0.1
F-e-HF	60.5 ± 10.6	65.9 ± 12.0	40.8 ± 6.9	48.5 ± 7.7	4.5 ± 2.4	2.8 ± 0.5
F-e-Other	14.8 ± 5.4	14.0 ± 4.8	19.6 ± 4.6	16.7 ± 4.9	3.4 ± 1.0	2.8 ± 1.7
F-m-HF	109.4 ± 15.4	127.0 ± 13.4	81.8 ± 9.7	83.0 ± 10.2	5.1 ± 0.9	5.5 ± 2.3
F-Other	27.1 ± 9.3	11.8 ± 5.8	9.4 ± 4.1	7.7 ± 3.3	4.0 ± 1.3	2.5 ± 1.0
Total	709.2 ± 21.3	602.6 ± 18.4	732.5 ± 20.6	608.8 ± 17.5	182.7 ± 9.1	154.1 ± 8.5

Table 7.14: Post-fit SR yields for the **Binary-3** fit.

The post-fit summary plot is presented in Figure 7.62. For the SRs, we observe a similar scenario with the **Binary-SRs** fit, with the *top* regions having more events than *antitop*.

SRs plots are presented in Figure 7.63. Once again, due to these regions' definition being a merge of the regions for the **Binary-SRs** fit, we observe the same phenomena. There are no significant differences in the shapes between the plots for the *top* quark regions and the *antitop* quark regions, except for the total number of events, which favours the *top* regions. Similarly, the only small differences are given by the use of $Q(\ell_W)$ in the training, a variable whose impact was quite high in the trainings.

The uncertainties on the POIs are presented in Figure 7.64. The MLE for the signal strength POI is $\mu(tZq) = 1.00 \pm 0.12 = 1.00^{+0.10}_{-0.09}(\text{stat})^{+0.08}_{-0.07}(\text{syst})$. Once again, theoretical

	CRFakesElHF		CRFakesElOther		CRFakesMuHF		CRFakesOther	
tZq	18.1 $\pm$ 2.4		2.1 $\pm$ 0.3		12.3 $\pm$ 1.5		0.9 $\pm$ 0.1	
$VV + b$	23.3 $\pm$ 5.2		3.0 $\pm$ 0.6		15.5 $\pm$ 3.3		1.1 $\pm$ 0.3	
$VV + c$	42.7 $\pm$ 7.2		29.8 $\pm$ 4.8		30.7 $\pm$ 5.2		13.1 $\pm$ 2.2	
$VV + l$	32.4 $\pm$ 5.5		214.6 $\pm$ 35.0		23.9 $\pm$ 4.3		87.5 $\pm$ 13.6	
$t\bar{t}Z$	54.7 $\pm$ 7.9		2.6 $\pm$ 0.4		35.0 $\pm$ 4.3		1.0 $\pm$ 0.2	
$t\bar{t}W$	5.2 $\pm$ 0.3		0.0 $\pm$ 0.0		0.0 $\pm$ 0.0		0.0 $\pm$ 0.0	
tWZ	4.2 $\pm$ 0.6		0.8 $\pm$ 0.1		2.4 $\pm$ 0.5		0.4 $\pm$ 0.1	
$t\bar{t}H$	25.2 $\pm$ 1.0		0.1 $\pm$ 0.0		12.4 $\pm$ 0.4		0.0 $\pm$ 0.0	
Other	338.7 $\pm$ 51.7		180.6 $\pm$ 59.7		85.0 $\pm$ 12.1		13.6 $\pm$ 6.6	
F-e-HF	10 056.1 $\pm$ 779.0		3165.9 $\pm$ 449.8		24.9 $\pm$ 4.7		6.5 $\pm$ 2.9	
F-e-Other	2211.2 $\pm$ 782.4		6038.9 $\pm$ 480.1		19.1 $\pm$ 12.7		15.7 $\pm$ 11.1	
F-m-HF	84.7 $\pm$ 24.3		50.7 $\pm$ 14.0		6865.2 $\pm$ 168.3		3173.1 $\pm$ 297.2	
F-Other	59.5 $\pm$ 18.7		44.8 $\pm$ 15.3		445.5 $\pm$ 136.1		1241.5 $\pm$ 307.8	
Total	12 956.2 $\pm$ 114.7		9733.8 $\pm$ 98.8		7571.9 $\pm$ 87.2		4554.6 $\pm$ 67.6	

Table 7.15: Post-fit Fakes CR yields.

systematics dominate the statistical uncertainty, contributing for 6%, with instrumental uncertainties accounting for 4.1%. Both these impacts are reduced with respect to the **Binary-SRs** fit. Both signal and prompt lepton background modelling contributions were increased to 5% and 3.3% respectively from the previous fit, opposed to the fake lepton background modelling impact which was reduced by two thirds. Once again, the signal modelling is dominated by the scale variation, whereas tZq PDF's impact was increased to 0.5%. Similarly, b -tagging uncertainties' impact was slightly reduced (1.3%), as well as MC statistics (1%), whereas luminosity's was increased to 0.8%. Overall, this fit performed better than **Binary-SRs**, with both up and down systematic uncertainties being 1% lower, resulting in the total uncertainty to be $\pm 12\%$. On the other hand, the uncertainties on the $t\bar{t}Z$ and FAKESLHF normalisation factors increased by 1%, whereas a 2% increase was observed for the FAKESLOTH NF.

The NP ranking for all six POIs is presented in Figure 7.66. In spite of the highest two ranked systematics being the same as the ones in Figure 7.61(a), the ranking for the signal strength presents multiple differences. The tZq showering impact was reduced by a third, falling to tenth place in the ranking. On the contrary, $t\bar{t}Z$ showering and scale variation for $VV + b$ contributions were almost doubled, becoming the third and fourth highest systematics. Moreover, all $t\bar{t}$ systematics impacts were reduced.

Analogously, the ranking for the $N_{t\bar{t}Z}$ POI presents multiple differences. First of all, we observe an overall increase in the impacts, which resulted in an increase in the total uncertainty on the NF. Secondly, the $VV + b$ scale variation is now the highest ranked variable, followed by $t\bar{t}Z$ showering, $t\bar{t}Z$ A14 and the tWZ modelling. Similar to the tZq signal strength, an overall reduction in the $t\bar{t}$ systematics impact is observed, whereas the b -tagging impact rose from 2 to 2.6%.

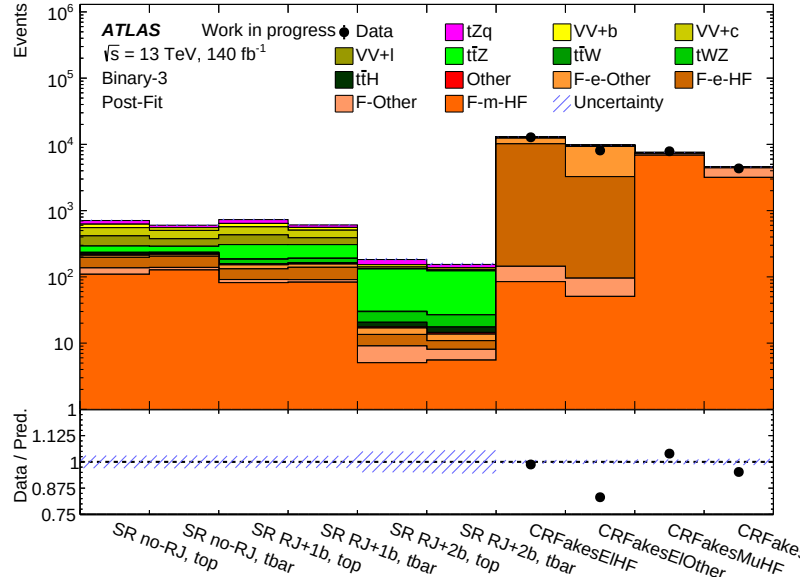


Figure 7.62: Post-fit summary plot displaying the yields in all the regions for the **Binary-3** fit.

On the other hand, the Fakes NFs present a similar ranking to the **Binary-SRs** fit, with the only exception being an overall increase in the impacts, which generates a higher uncertainty on the NFs.

Finally, the same constraints of the **Binary-SRs** fit are observed. The tZq showering has a constraint of 0.35, the $t\bar{t}$ generator MuHF systematic has a constraint of around 0.5 and other smaller constraints on the other $t\bar{t}$ generator, shower and h_{damp} are present as well. Analogous to the **Binary-SRs** fit, an anticorrelation of -51% was observed between $t\bar{t}$ generator EIOther and $t\bar{t}$ generator EIHF.

Summarising, this fit used 186 NPs and 6 POIs. 6 SRs and 4 CRs were defined, each with 10 bins, resulting in 100 total bins, 40 less than the **Binary-SRs** fit. The total uncertainty on the signal strength is $\pm 12\%$. The difference between this uncertainties and the one of the **Binary-SRs** fit is of 0.5%, therefore it is hard to say confidently that this fit performed better than the other. Nevertheless, this fit produces a total uncertainty on the signal strength of $\pm 12\%$, which is a 20% improvement with respect to the 15% obtained with the old analysis.

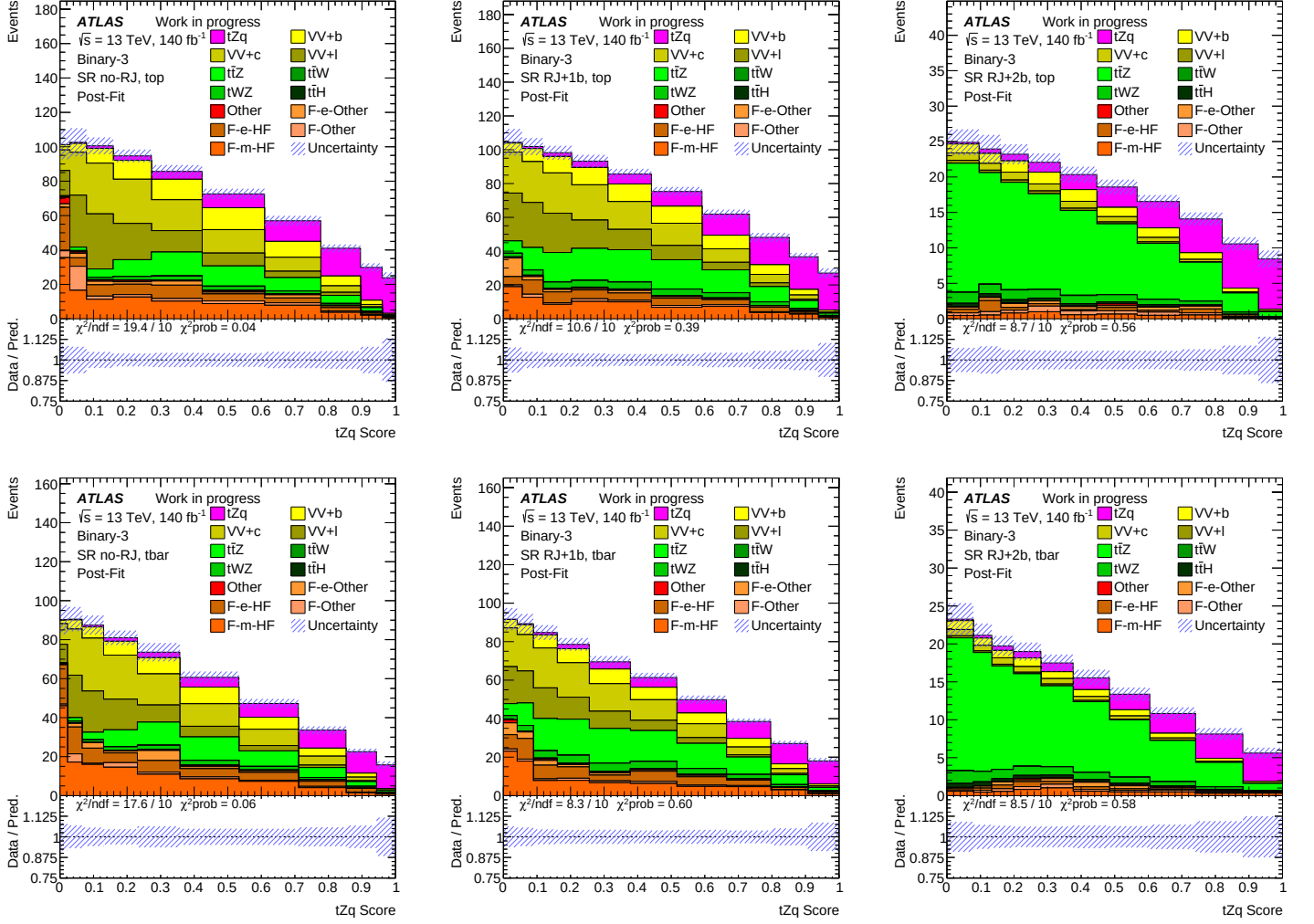


Figure 7.63: Post-fit SRs plots for the Binary-3 fit, displaying *top* quark regions (top) and *antitop* quark regions (bottom).

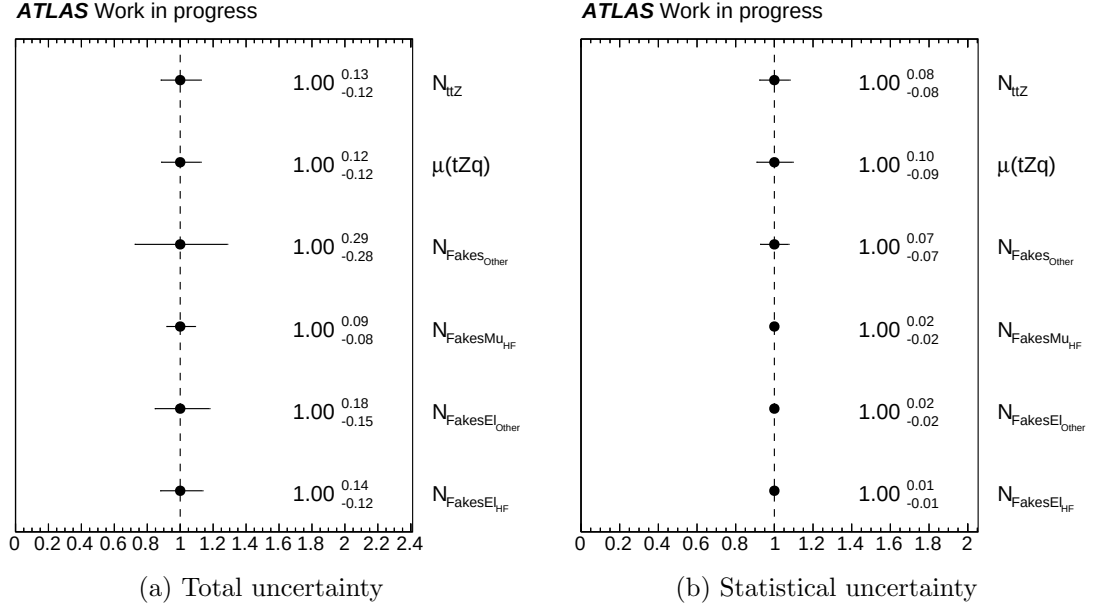


Figure 7.64: POI total uncertainty (left) and stat-only uncertainty (right) for all the POIs in the Binary-3 fit.

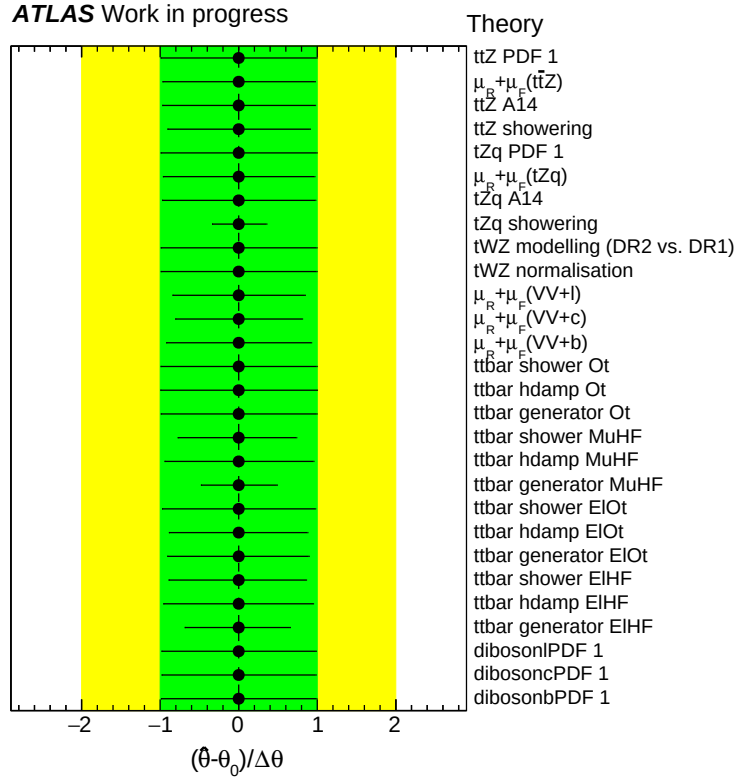


Figure 7.65: Pull plot for the theoretical systematics in the Binary-3 fit.

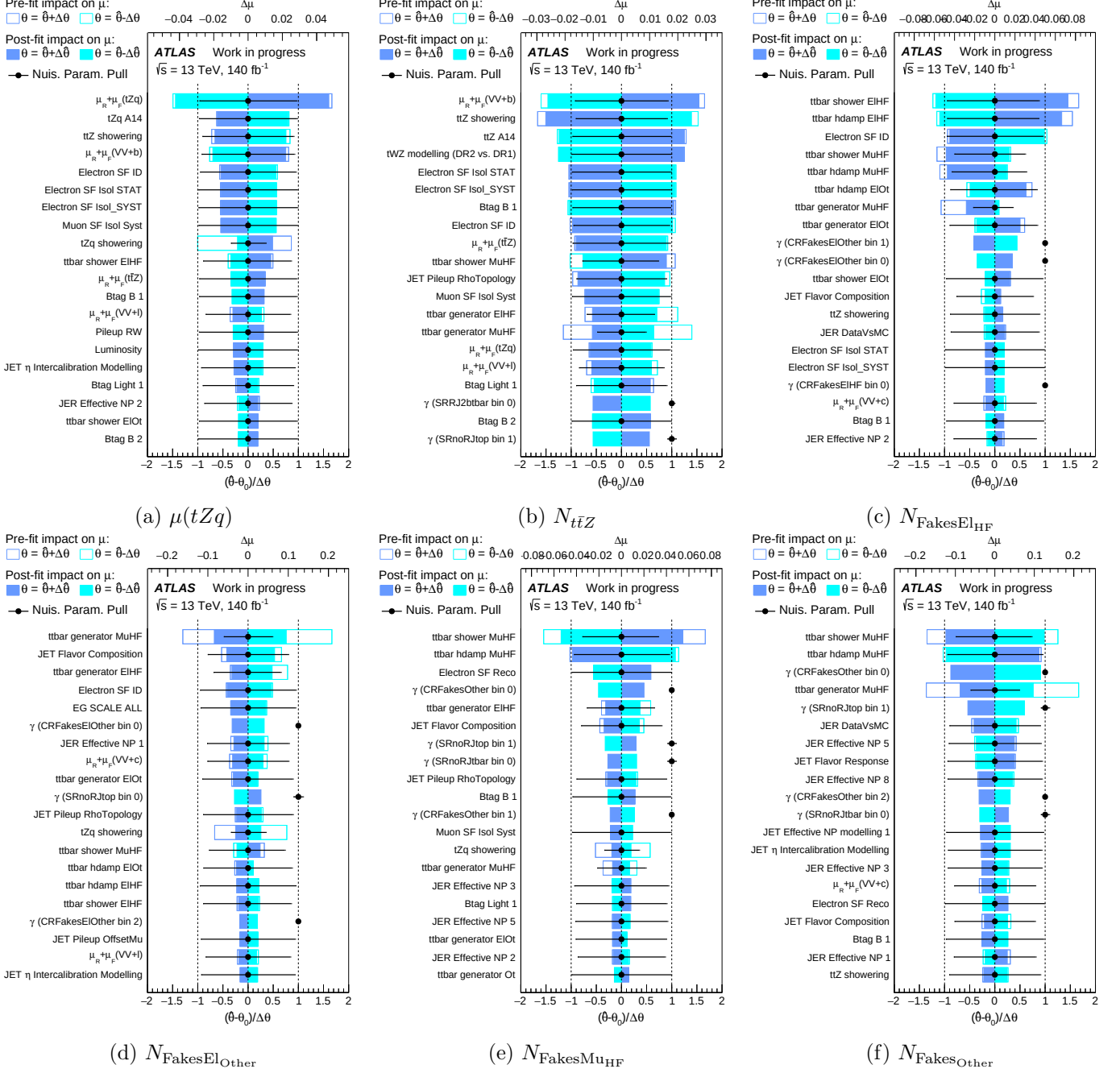


Figure 7.66: NP ranking for the six POIs in the Binary-3 fit.

7.3.3 MC-mixed

Finally, I will present the fit performed using the same setup described in Section 7.2.3. For this fit, two different MC-3 NNs were trained, one for events with 1 b -jet and one for events with 2 b -jets. In the former, the targets are signal, VV , and *Others*, whereas in the latter the targets are signal, $t\bar{t}Z$, and *Others*. Before describing the fit, it must be noted that the regions labelled as “CRs” in the MC-mixed fit (Section 7.2.3), are treated the same of the signal regions by the fit, in spite of being labelled as control regions. This is due to the signal contribution in those regions being non-negligible, as it is with “real” CRs, such as the four Fakes CRs. Therefore, in order to avoid confusion, these regions will be labelled as SRs, even if they are regions in which the greatest component comes from a specific group of background, whereas the Fakes CRs will be treated as real CRs and thus will have data visible.

	SR tZq , 1b, t	SR VV , 1b, t	SR <i>Others</i> , 1b, t	SR tZq , 2b, t	SR $t\bar{t}Z$, 2b, t	SR <i>Others</i> , 2b, t
tZq	128.9 ± 13.5	16.9 ± 2.1	9.8 ± 1.5	43.0 ± 6.1	4.8 ± 0.8	4.3 ± 0.6
$VV + b$	58.2 ± 11.2	52.5 ± 9.8	21.6 ± 4.2	9.8 ± 2.4	5.1 ± 1.2	7.1 ± 1.6
$VV + c$	42.9 ± 7.2	211.7 ± 31.5	15.4 ± 2.5	3.4 ± 0.6	1.5 ± 0.3	8.2 ± 1.5
$VV + l$	18.9 ± 3.3	215.0 ± 33.0	11.4 ± 1.5	0.5 ± 0.2	0.2 ± 0.1	3.4 ± 0.9
$t\bar{t}Z$	60.2 ± 6.3	34.1 ± 3.9	47.7 ± 5.4	44.7 ± 5.0	79.6 ± 6.9	14.1 ± 1.4
$t\bar{t}W$	0.4 ± 0.0	0.2 ± 0.0	0.4 ± 0.0	0.3 ± 0.0	0.1 ± 0.0	0.3 ± 0.0
tWZ	15.3 ± 2.1	10.6 ± 1.5	9.3 ± 1.3	4.9 ± 1.1	6.0 ± 1.5	2.3 ± 0.6
$t\bar{t}H$	1.6 ± 0.1	0.8 ± 0.0	1.7 ± 0.1	1.6 ± 0.1	1.7 ± 0.1	1.1 ± 0.1
Other	1.1 ± 0.2	0.8 ± 0.2	6.8 ± 1.5	0.5 ± 0.1	0.1 ± 0.1	1.1 ± 0.2
F-e-HF	20.2 ± 6.9	8.7 ± 3.7	69.9 ± 10.2	1.7 ± 1.0	0.5 ± 0.3	4.8 ± 1.2
F-e-Other	4.7 ± 1.6	4.0 ± 1.6	22.6 ± 6.1	2.2 ± 1.2	0.9 ± 0.8	3.4 ± 0.6
Total	396.1 ± 14.8	575.4 ± 18.3	370.1 ± 15.4	118.6 ± 6.0	102.7 ± 6.2	61.6 ± 3.3
Signal %	32.6%	2.9%	2.7%	36.3%	4.7%	7.0%
Target %	32.6%	83.3%	84.3%	36.3%	77.5%	70.1%

	SR tZq , 1b, $\bar{t}$	SR VV , 1b, $\bar{t}$	SR <i>Others</i> , 1b, $\bar{t}$	SR tZq , 2b, $\bar{t}$	SR $t\bar{t}Z$, 2b, $\bar{t}$	SR <i>Others</i> , 2b, $\bar{t}$
tZq	69.8 ± 7.3	11.5 ± 1.4	7.6 ± 1.1	22.5 ± 3.5	4.1 ± 0.7	2.8 ± 0.4
$VV + b$	37.6 ± 6.9	38.9 ± 7.3	17.3 ± 3.5	6.0 ± 1.4	4.4 ± 1.1	4.4 ± 1.0
$VV + c$	34.8 ± 5.7	189.9 ± 27.7	14.4 ± 2.5	2.3 ± 0.5	1.6 ± 0.4	6.1 ± 1.1
$VV + l$	9.9 ± 1.8	149.4 ± 22.8	8.8 ± 1.2	0.3 ± 0.1	0.2 ± 0.1	2.2 ± 0.6
$t\bar{t}Z$	51.2 ± 5.3	32.2 ± 3.9	51.9 ± 6.1	36.2 ± 4.1	83.5 ± 7.2	12.0 ± 1.1
$t\bar{t}W$	0.3 ± 0.0	0.1 ± 0.0	0.2 ± 0.0	0.2 ± 0.0	0.1 ± 0.0	0.1 ± 0.0
tWZ	13.6 ± 1.6	10.5 ± 1.6	11.0 ± 1.5	4.2 ± 0.9	6.9 ± 1.6	2.0 ± 0.5
$t\bar{t}H$	1.4 ± 0.1	0.8 ± 0.0	2.0 ± 0.1	1.4 ± 0.1	1.9 ± 0.1	1.1 ± 0.1
Other	0.7 ± 0.8	0.5 ± 0.1	3.0 ± 1.8	0.5 ± 0.1	0.2 ± 0.1	0.8 ± 0.2
F-e-HF	20.2 ± 3.5	8.8 ± 4.0	81.8 ± 12.2	1.7 ± 0.6	0.5 ± 0.2	4.2 ± 1.0
F-e-Other	3.7 ± 2.7	9.3 ± 3.3	15.0 ± 4.6	1.5 ± 0.7	0.6 ± 0.6	1.9 ± 1.0
Total	280.9 ± 10.1	473.5 ± 15.2	374.1 ± 16.0	81.1 ± 4.1	106.2 ± 6.5	48.4 ± 3.5
Signal %	24.8%	2.4%	2.0%	27.7%	3.9%	5.8%
Target %	24.8%	79.8%	87.2%	27.7%	78.6%	69.4%

Table 7.16: Post-fit SR yields for the MC-mixed fit.

Analogous to what done with the other two fits with the complete set of systematics, we have split the SRs regions based on the charge of ℓ_W . Consequently, 12 SRs were used, alongside the 4 Fakes CRs, whose post-fit yields are presented in Tables 7.16 and 7.17. It

	CRFakesElHF		CRFakesElOther		CRFakesMuHF		CRFakesOther	
tZq	18.1 ±	2.9	2.1 ±	0.4	12.3 ±	1.6	0.9 ±	0.2
$VV + b$	23.3 ±	4.9	3.0 ±	0.6	15.5 ±	3.1	1.1 ±	0.2
$VV + c$	42.7 ±	6.8	29.8 ±	4.6	30.7 ±	4.9	13.1 ±	2.2
$VV + l$	32.4 ±	5.2	214.6 ±	33.6	23.9 ±	4.0	87.5 ±	13.0
$t\bar{t}Z$	54.7 ±	7.0	2.6 ±	0.4	35.0 ±	3.8	1.0 ±	0.2
$t\bar{t}W$	5.2 ±	0.3	0.0 ±	0.0	0.0 ±	0.0	0.0 ±	0.0
tWZ	4.2 ±	0.6	0.8 ±	0.1	2.4 ±	0.5	0.4 ±	0.1
$t\bar{t}H$	25.2 ±	1.1	0.1 ±	0.0	12.4 ±	0.4	0.0 ±	0.0
Other	338.7 ±	50.3	180.6 ±	57.7	85.0 ±	11.7	13.6 ±	5.7
F-e-HF	10 056.1 ±	784.9	3165.9 ±	457.7	24.9 ±	4.7	6.5 ±	2.8
F-e-Other	2211.2 ±	790.3	6038.9 ±	487.2	19.1 ±	12.8	15.7 ±	10.8
Total	12 956.2 ± 114.6		9733.8 ± 98.5		7571.9 ± 87.3		4554.6 ± 67.5	

Table 7.17: Post-fit Fakes CRs yields for the MC-mixed fit.

is clear how this time the splitting between the *top* and *antitop* components has an effect on the purity of the regions. The *top* quark regions are more pure for signal and Diboson, because these two processes favour process with $Q(\ell_W) = +1$. On the other hand, SRs $t\bar{t}Z$ and *Others* 1b, which is mostly $t\bar{t}Z$ and Fakes, are more pure in the *antitop* regions, because less signal and Diboson will be in there. In detail, the *top* tZq SRs have a higher purity (33% and 36%) than when the *top/antitop* splitting was not applied (29% and 32%). Contrarily, the *antitop* tZq SRs are less pure, with a signal contribution of 25% and 28% in the 2b region.

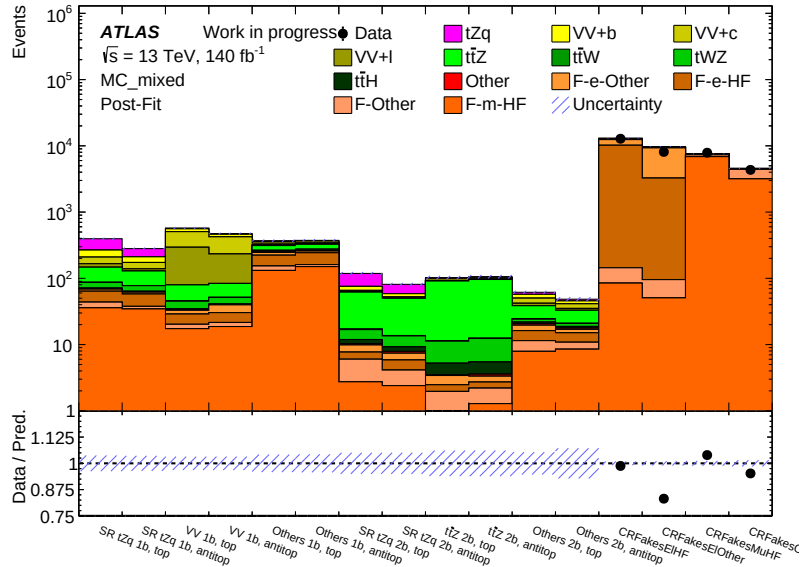


Figure 7.67: Post-fit summary plot displaying the yields in all the regions for the MC-mixed fit.

The summary plot is presented in Figure 7.67. In the regions in which either signal or Diboson are present, we observe a significant difference between *top* and *antitop* yields, whereas in regions in which they are negligible, such as the *Others 1b* region and the *th tZ 2b* region, the yields are either equal or in favour of the *antitop* regions.

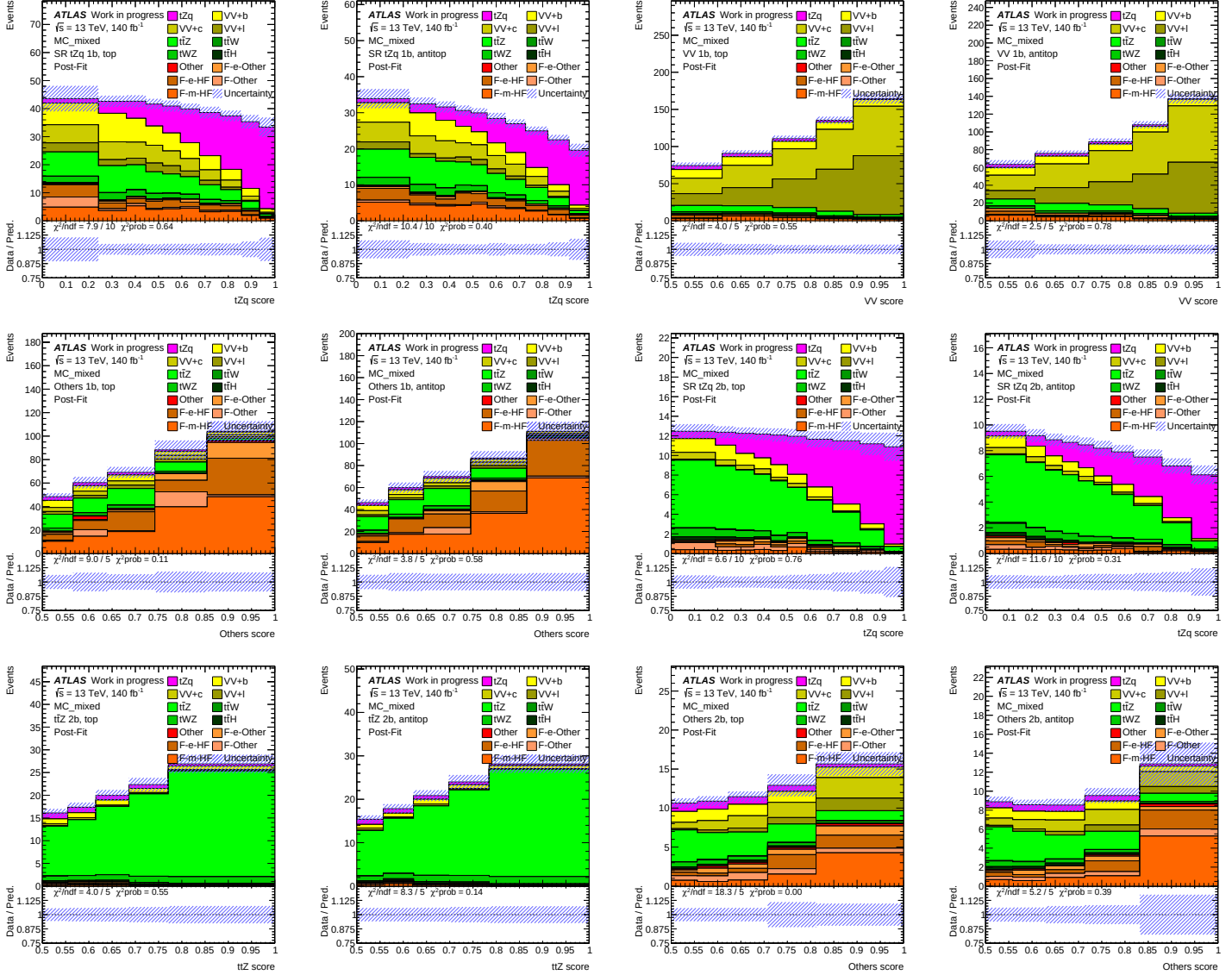


Figure 7.68: Post-fit SRs plots for the MC-mixed fit.

Post-fit SRs plots are presented in Figure 7.68. For the aforementioned reasons, we observe some differences between the *top* and the *antitop* region, even if the shape is the same due to them being trained together. The differences are mainly in the number of target events in the last bins. For the *tZq* SRs, we note a clear decrease in said events going from the *top* region to the *antitop*. Analogously, the *VV 1b* and the *Others 2b* regions, due to the presence of Diboson, present the same situation. On the other hand,

the remaining SRs have similar target events in the last bin, since they are dominated by $t\bar{t}Z$ and Fakes.

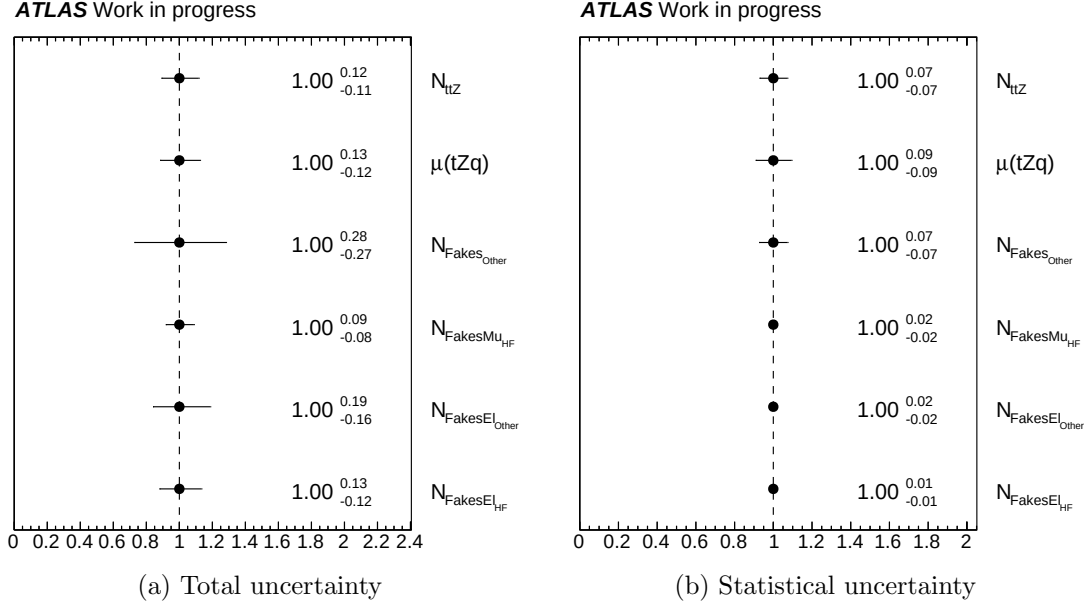


Figure 7.69: POI total uncertainty (left) and stat-only uncertainty (right) for all the POIs in the MC-mixed fit.

Figure 7.69 displays the uncertainties on all POIs. The MLE for the signal strength is $\mu(tZq) = 1.00^{+0.13}_{-0.12} = 1.00 \pm 0.09(\text{stat})^{+0.08}_{-0.07}(\text{syst})$, comparable with **Binary-SRs** but greater than **Binary-3**. Once again, theoretical uncertainties contribute more than instrumentals', 6.2% versus 4.6%. Among the systematics, the greatest impact come from signal modelling (5.1%), dominated by the scale variations, prompt lepton background modelling (3.8%), and leptons (3.5%), similarly to the **Binary-3** fit. Uncertainties on the signal PDF account for 0.5%, whereas MC statistics contribution was increased to 1.3%. Finally, luminosity's impact increased to 0.9%, the highest among the three complete fits, whereas all b -tagging uncertainties accounted for 1.4%, comparable with the other fits. The uncertainties on the other POIs are comparable to the ones extracted from the **Binary-SRs** fit, overall smaller than the **Binary-3** fit.

NPs ranking plot for all POIs are presented in Figure 7.71. Overall, they are similar to the rankings in the **Binary-3** fit. For the signal strength, the eight variables contributing more are the same as the **Binary-3** fit, with the only difference being a greater impact from $t\bar{t}Z$ showering with respect to tZq A14. tZq showering contribution was reduced, as was also its constraint, and its impact has switched sign, meaning an increase in the showering produced a decrease in the signal strength, whereas in previous fits the opposite situation was observed. Other variables' ranking remained in general the same.

Regarding the $t\bar{t}Z$ NF, we observe only a significant decrease in the tWZ modelling contribution, as well as a rise in $t\bar{t}Z$ showering impact, which contributes at 4%. Overall, other systematics' impacts remained the same. Similarly, the NPs ranking for the Fakes

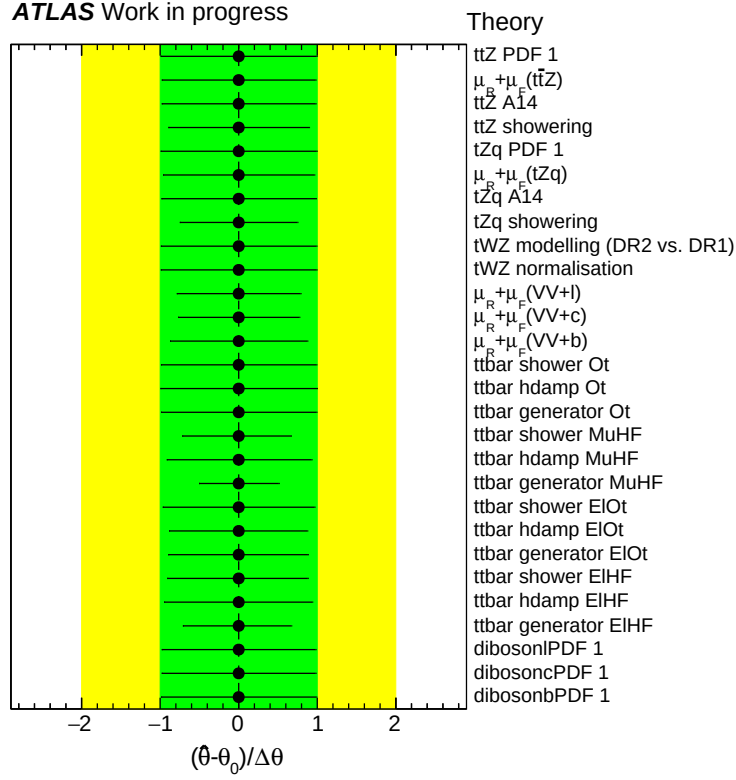


Figure 7.70: Pull plot for the theoretical systematics in the MC-mixed fit.

POIs present the same results as the ones in the previous two fits.

Nevertheless, this fit has much smaller constraints on the both the $t\bar{t}$ systematics and the tZq showering, with the latter being expected because the regions are not split based on jet multiplicity. As far as the correlations between systematics go, we observe the same situation as the previous two fits.

In summary, this fit used a 12 SRs and 4 Fakes CRs, for a total of 120 bins. 186 NPs were defined, as well as 6 POIs. The total uncertainty on the signal strength is +13%, -12%, in between **Binary-3**, which remain the better fit, and **Binary-SRs**.

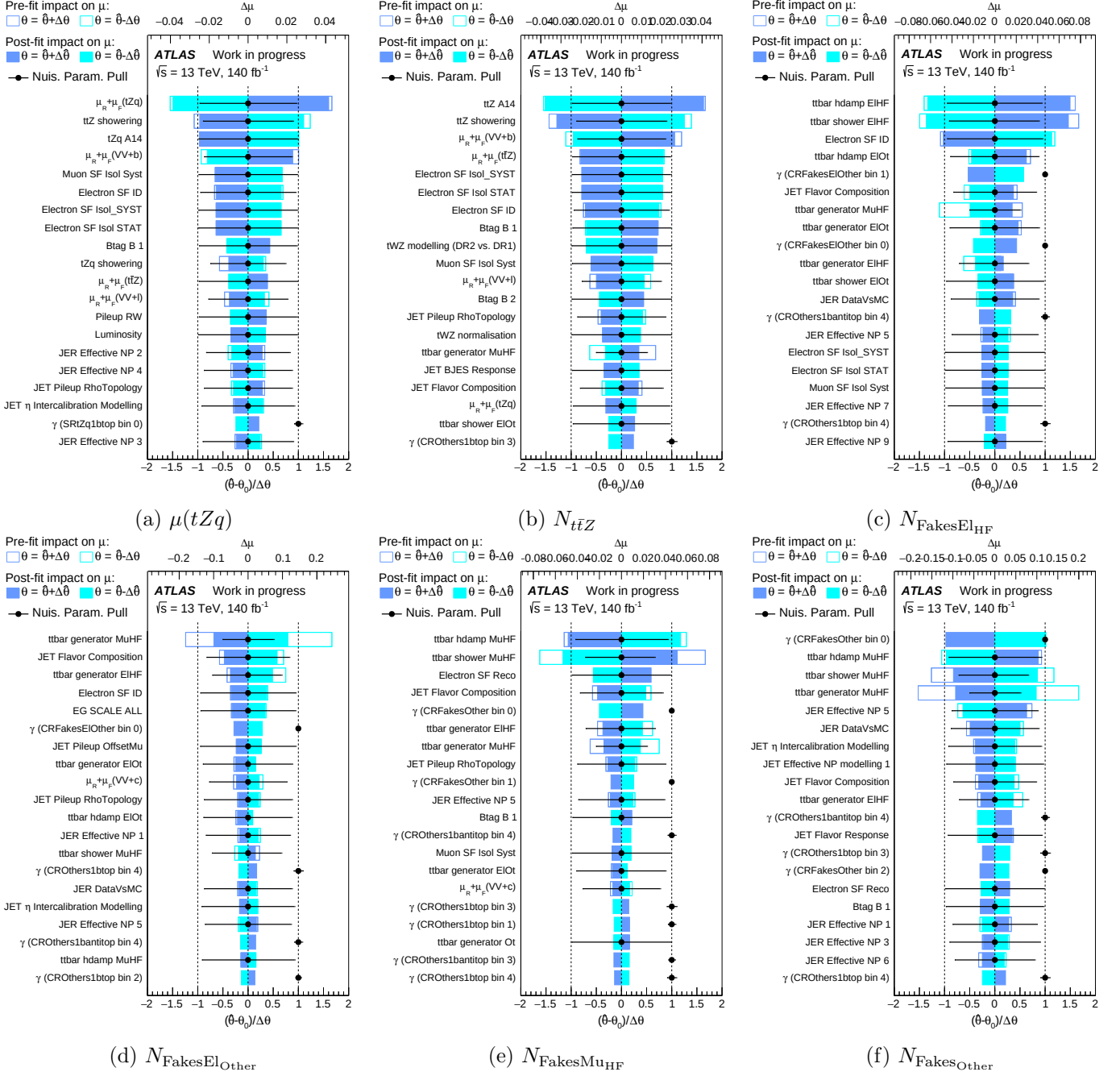


Figure 7.71: NP ranking for the six POIs in the MC-mixed fit.

7.3.4 Summary

Three different setups were used for the fits with the complete set of systematics, which used conceptually different ideas.

The **Binary-SRs** fit was made using a NN in which the entire dataset was used for the training, which is the simplest configuration available. The fit was made splitting regions in the trainings based on jet multiplicity, which is the same setup used in the old analysis, though at the time the 5 jets and the $4j1b$ regions were not used.

The **Binary-3** fit presents a more complex setup. The idea of this fit is to exploit the different shapes of the sources in different jet multiplicity regions. Therefore, three different Binary trainings were made, each using only similar jet multiplicity regions. With this setup, the training performance was deteriorated, in spite of less statistics given to the training, and also the fit performed better, because the regions used for the fit were the same regions used for the training.

Finally, the **MC-mixed** fit was made using the most complex setup. Multi Class NNs allow to define background-enhanced regions for the fit, which are useful to better control some specific backgrounds. However, the cost of using a Multi Class is that the training performance is worse than the Binary. This last fit was made with an improved version of the Multi Class training, in which the whole dataset was split based on the number of b -jets, and in the two regions two different Multi Class NNs were implemented, using different targets. This has proven to give better results than the other fits made with a Multi Class.

Overall, all these three fits' performances were similar, and thus there is no clear evidence of a setup being better than the others. Nevertheless, the **Binary-3** fit produced the lower uncertainty on the signal strength, $\pm 12\%$, whereas the other two uncertainties were $+13\%$, -12% . The difference between the three is minimal, as it is possible that simply by changing the number of bins the results could switch. However, this difference is there. Therefore, as a final result for the inclusive cross section we decided to use this one, since it is the most precise. Moreover, we have used this setup also for the other cross section measurements presented in this thesis, which are the *top* and *antitop* separate associated Z boson production cross sections, as well as their ratio.

Chapter 8

Top, antitop and ratio cross section measurements

Finally, I will focus on the presentation of ATLAS' first measurement of the ratio between the *top* and *antitop* quark separate cross section production in the tZq channel. The advantage of measuring the ratio between two cross sections is that there are some uncertainties which cancel out, for instance the luminosity. Moreover, because the tZq process occurs through the t -channel single *top* quark production, this measurement allows us to validate the t -channel measured ratio of $1.636^{+0.036}_{-0.034}$ [95]. Furthermore, the ratio is an interesting measurement because it depends on the internal structure of the proton, and therefore measuring it allows to probe the PDFs. Alongside the ratio, the cross sections for the two production process (tZq or $\bar{t}Zq$) independently have been measured.

In order to perform these measurements, three different fits must be done. The first fit measures the inclusive cross section for both *top* and *antitop* together. This fit is the same as the fits presented in Section 7.3, in which the regions were split based on $Q(\ell_W)$. The second fit is used to measure the cross sections of tZq and $\bar{t}Zq$ separately. This is done by also splitting the signal sample in two samples, one with $Q(\ell_W) = +1$, and one with opposite charge. The two cross sections are then measured by setting two POIs for the signal strength, one for tZq and one for $\bar{t}Zq$, and they are independent because in the regions with tZq there is no $\bar{t}Zq$ and vice versa. Finally, the third fit is used to measure the ratio between the two cross sections, defined as $R(t/\bar{t}) = \sigma(tZq)/\sigma(\bar{t}Zq)$. Alongside this, the fit also provides a measurement of the *antitop* cross section, which is used for cross-checking the result obtained with the second fit.

These three fits are made using the same 186 NPs used for the fits in Section 7.3. Additionally, two POIs were added to the 4 Fakes and the $t\bar{t}Z$ NFs. For the ratio fit, the POIs are the ratio between the cross sections and the *antitop* signal strength, whereas the other fit uses the signal strengths of *top* and *antitop* separately.

These measurements have been performed for all three fits presented in Section 7.3, but since the results were comparable, only the **Binary-3** fit will be presented, since its total cross section uncertainty was lower than the other two. Furthermore, because

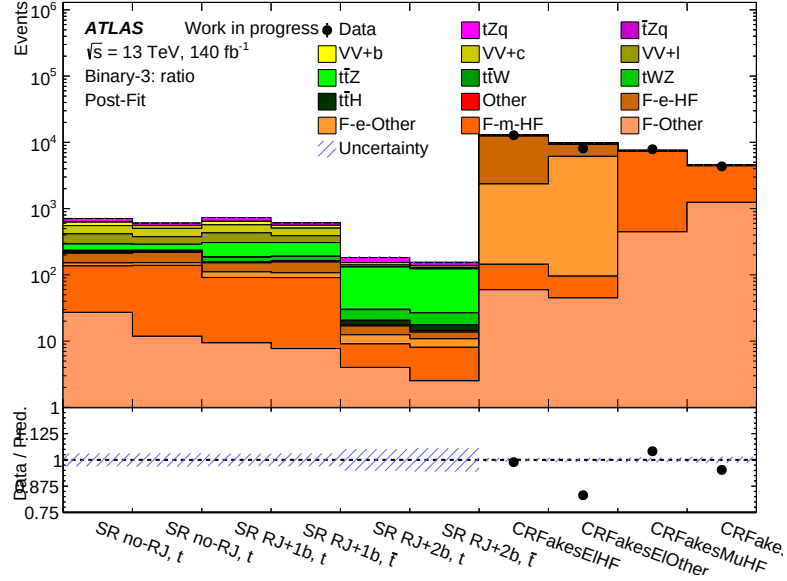


Figure 8.1: Post-fit summary plot for the Binary-3 fit aiming at measuring ratio and the two cross sections independently.

the setup is the same as the one presented in Section 7.3.2, I will not be showing yields and regions plots, because they are the same as the ones displayed in Tables 7.14 and 7.15 and Figure 7.63. As a remainder, only the post-fit summary plot is presented (Figure 8.1).

For these fits, all POIs are set to 1, even the ratio. Though this might seem like an error, since the ratio is predicted to be 1.67, this is actually the correct way to do it, because the ratio POI is the actually the ratio between the signal strengths of top and $antitop$. Therefore, since the signal strengths are set to 1 in these blind fits, the ratio POI is set to 1 as well.

The total and statistical-only uncertainties for the POIs are presented in Figures 8.2 and 8.3, respectively for the $top/antitop$ and the ratio fit. First of all, from Figure 8.2 we can see how the cross section for the top quark production has a lower uncertainty, due mostly to the higher statistics that the top has with respect to the $antitop$. Moreover, from the comparison between Figures 8.2 and 8.3, we can see that the $antitop$ $\bar{t}Zq$ cross section uncertainty is the same, thus confirming the accuracy of the two fits. The MLE for the three POIs are presented in Equation (8.0.1).

$$\begin{aligned}
 \mu(tZq, t) &= 1.00^{+0.14}_{-0.13} = 1.00 \pm 0.11(\text{stat}) \pm 0.07(\text{syst}) \\
 \mu(tZq, \bar{t}) &= 1.00^{+0.20}_{-0.18} = 1.00^{+0.17}_{-0.16}(\text{stat}) \pm 0.09(\text{syst}) \\
 R(t/\bar{t}) &= 1.00^{+0.23}_{-0.18} = 1.00^{+0.22}_{-0.17}(\text{stat}) \pm 0.06(\text{syst})
 \end{aligned} \tag{8.0.1}$$

All three are statistically dominated, with the latter being the most stat-dominated because many systematics cancel out when doing the ratio. The systematics impact on the two separate cross sections is the same, with the only difference being a greater impact on

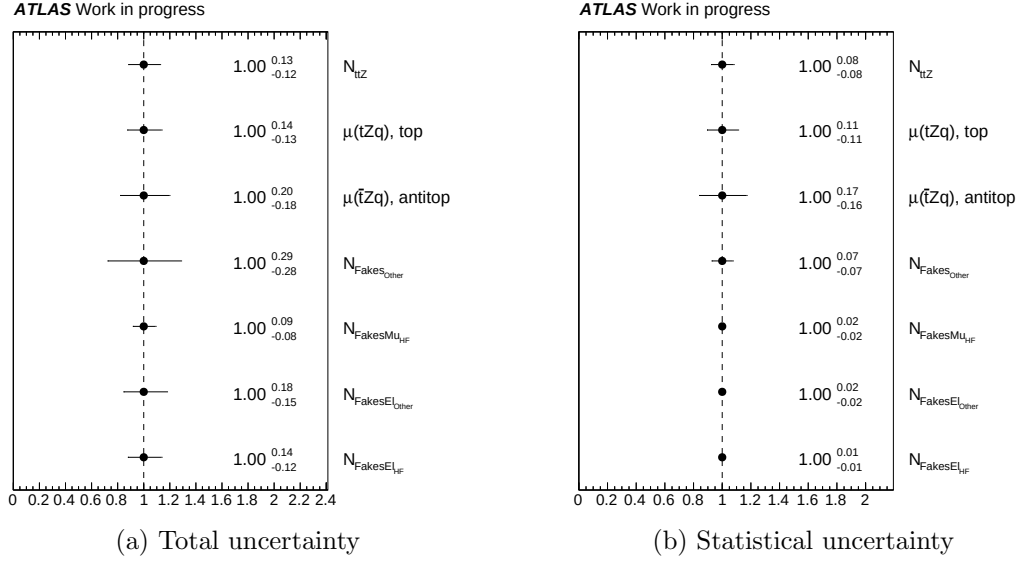


Figure 8.2: POI total uncertainty (left) and stat-only uncertainty (right) for the Binary-3 $top/antitop$ fit.

the $\bar{t}Zq$ cross section. In Table 8.1 the impacts of all systematics are presented, with also the comparison for the inclusive cross section.

Systematic	Inclusive	Top	$Antitop$	Ratio
tZq modelling	5.0%	4.8%	5.7%	1.0%
Prompt bkg modelling	3.3%	3.0%	4.2%	1.7%
Leptons	3.3%	3.2%	3.6%	0.5%
Jets	1.6%	1.6%	2.2%	1.6%
Fake bkg modelling	1.6%	2.5%	2.9%	4.6%
b -tagging	1.3%	1.4%	1.4%	0.8%
MC statistics	1.0%	1.3%	2.4%	2.7%
Luminosity	0.8%	0.8%	0.8%	< 0.1%
Pileup	0.8%	0.9%	0.8%	0.07%
tZq PDF	0.3%	0.4%	0.6%	0.2%
Theory	6.1%	6.1%	7.5%	5.1%
Instrumental	4.1%	4.2%	5.0%	2.9%
Full systematics	7.4%	7.4%	9.0%	5.9%
Statistical	9.5%	11%	16.5%	19.5%
Total	12%	13.5%	19%	20.5%

Table 8.1: NPs grouped impact to the uncertainty on inclusive cross section, top only cross section, $antitop$ only cross section and $top/antitop$ cross sections ratio.

Overall, we note that the ratio is the one with the lower systematic uncertainty, but it has the highest statistical one. Top only and inclusive have almost the same contributions

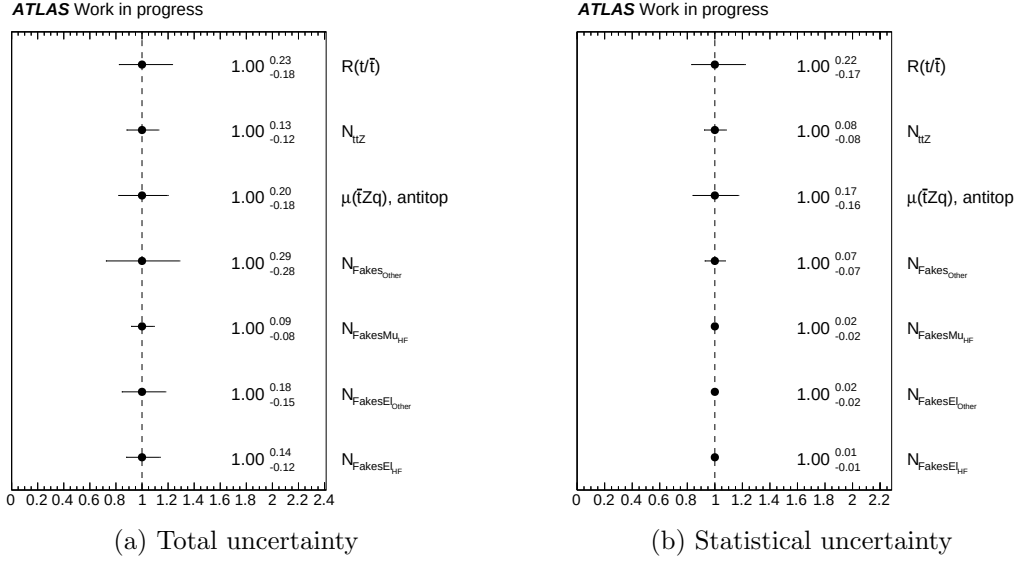


Figure 8.3: POI total uncertainty (left) and stat-only uncertainty (right) for the **Binary-3** ratio fit.

for all systematics, with the former having a greater total uncertainty due to the reduced statistics. On the other hand, the *antitop* cross section is the one with greater systematics uncertainty, accompanied by an increased statistical uncertainty with respect to *top* cross section because less events are used for its measurement.

The NP rankings for *top*, *antitop* and ratio are presented in Figure 8.4. Some similarities can be observed for the rankings of *top* and *antitop* signal strengths, whereas the ratio ranking is dominated by systematics which do not appear in the previous two rankings. This is due to this POI being a ratio of the other two POIs, and thus the common systematics are cancelled out.

Furthermore, the pull plots for the *top/antitop* fit (Figure 8.5(a)) and for the ratio fit (Figure 8.5(b)) are presented. For both fits we observe the same significant constraint on the *tZq* showering observed in the **Binary-3** fit (Figure 7.65), as well as the usual smaller constraints.

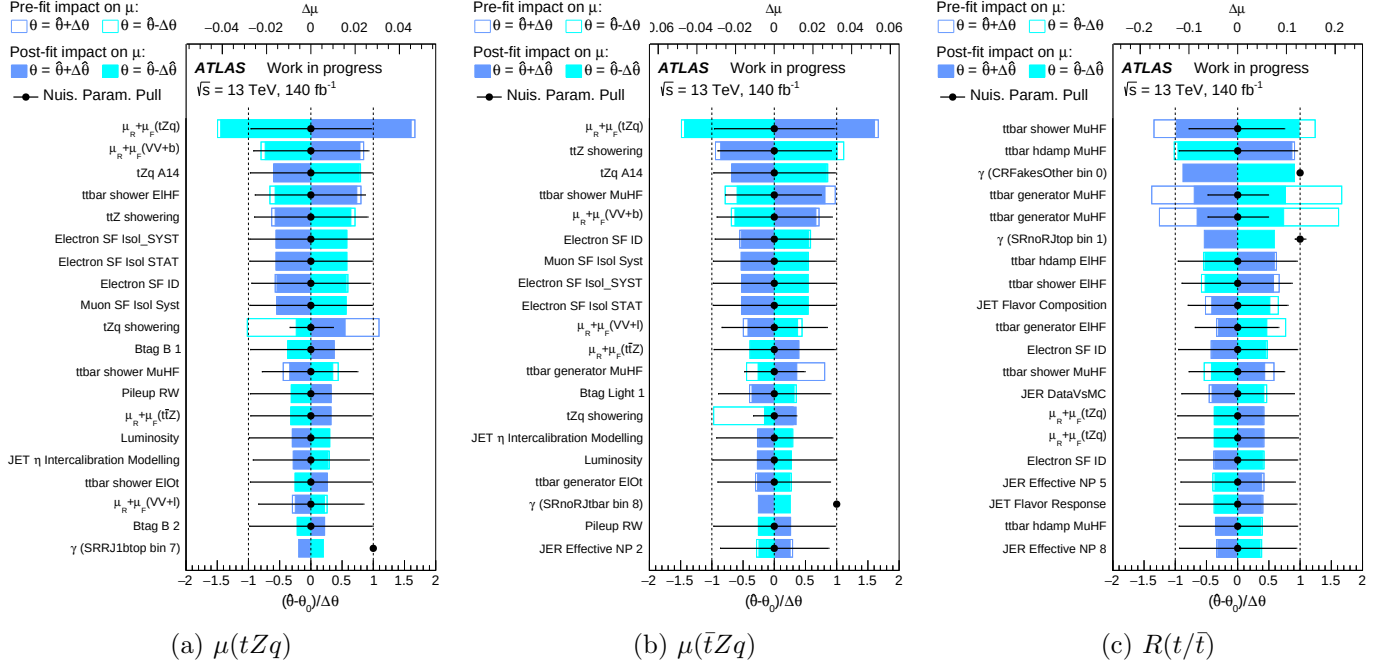


Figure 8.4: NP ranking for *top* only signal strength (left), *antitop* only signal strength (centre) and ratio (right).

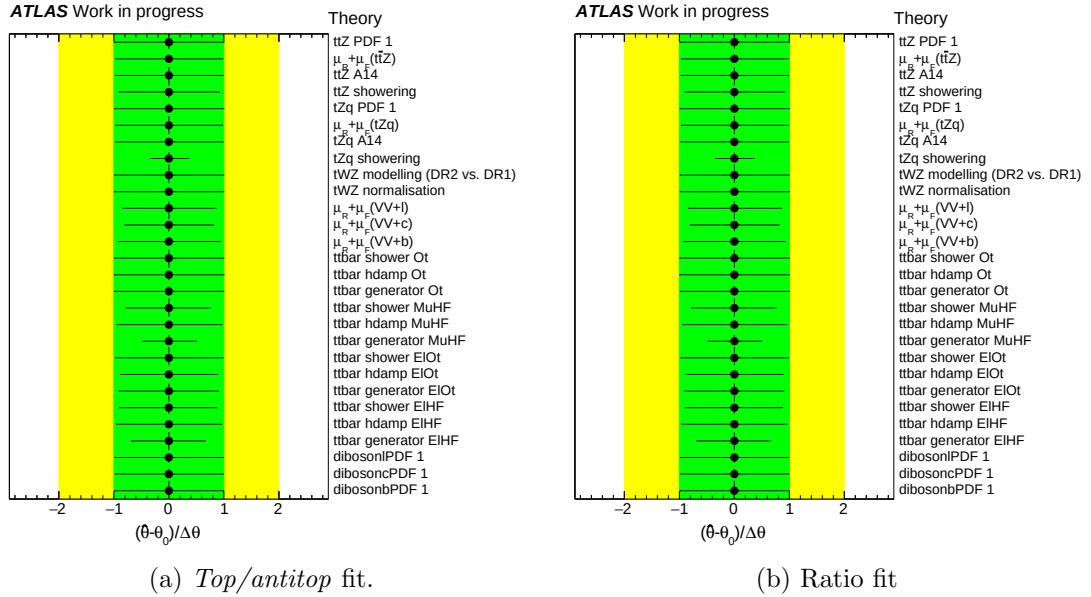


Figure 8.5: Pull plot for the *top/antitop* (left) and the ratio (right) fits.

Chapter 9

Conclusions

In this thesis we developed a refined analysis for the inclusive cross section measurement of the single *top* quark associated production with a *Z* boson, which was the aim of this project. ATLAS' previous measurement was $\sigma_{tZq}^{\text{Observed}} = 97^{+14}_{-13} \text{ fb} = 97^{+13}_{-12}(\text{stat}) \pm 7(\text{syst}) \text{ fb}$ [46], which has a relative 15% uncertainty, and was in good agreement with the SM prediction of $\sigma_{tZq}^{\text{Theory}} = 101.7^{+5.3}_{-1.3}(\text{scale}) \pm 1.1(\text{PDF}) \text{ fb}$.

The cross section is extracted by doing a *binned profile Likelihood* fit to the output of the Neural Networks trained in Chapter 6. In the fits, presented in Chapter 7, the signal strength $\mu(tZq)$, defined as the ratio between measured and predicted cross section, was set as the parameter of interest. The fits are blind, meaning real collision data is replaced by the sum of signal and background expectations from Monte Carlo. Therefore, the extracted signal strength will be 1, and we are interested in its uncertainty.

Overall, the best result obtained for the signal strength is $\mu(tZq) = 1.00 \pm 0.12 = 1.00^{+0.10}_{-0.09}(\text{stat})^{+0.08}_{-0.07}(\text{syst})$. The $\pm 12\%$ uncertainty on the inclusive cross section represents a 20% improvement with respect to the previous analysis.

Furthermore, I developed an analysis for the separate measurement of the *tZq* and *antitZq* cross section, as well as their ratio. This represents the first attempt done in ATLAS of this measurement. These three parameters were measured with the same fit setup used for the inclusive cross section, as described in Chapter 8. The *top* only inclusive signal strength MLE is $\mu(tZq, t) = 1.00^{+0.14}_{-0.13} = 1.00 \pm 0.11(\text{stat}) \pm 0.07(\text{syst})$, the *antitop* only is $\mu(tZq, \bar{t}) = 1.00^{+0.20}_{-0.18} = 1.00^{+0.17}_{-0.16}(\text{stat}) \pm 0.09(\text{syst})$ and finally the ratio is $R(t/\bar{t}) = 1.00^{+0.23}_{-0.18} = 1.00^{+0.22}_{-0.17}(\text{stat}) \pm 0.06(\text{syst})$.

The uncertainties on the three measurements are comparable with CMS' values [61], which represent the most precise measurements to date of the two separate cross section and their ratio in the *tZq* process.

In conclusion, this thesis paves the way for ATLAS' most precise *tZq* cross section measurement, which is expected to be obtained once the analysis will be unblinded. Moreover, it presents the development of the analysis for the first measurements in ATLAS of

the inclusive tZq cross sections separately for top and $antitop$ quark, alongside their ratio. When the fit will be made to data, we expect these three measurements to be the most precise for the tZq process, since the expected relative uncertainties are lower than CMS’.

Additionally, this thesis provides three different converging fit setups which return the same uncertainty on the inclusive cross section, both for top and $antitop$ separately and combined, and on the ratio. Currently, we are using these fits aiming at presenting ATLAS’ first differential cross section measurement for the tZq process.

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