Charged particle distributions and robustness of the neural network pixel clustering in ATLAS

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Licentiate Thesis in Physics
Stockholm, Sweden 2016
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Cover illustration: Artist’s impression of a proton-proton collision. Created by Isa Håkansson.
Abstract

This thesis contains a study of the robustness of the artificial neural network used in the ATLAS track reconstruction algorithm as a tool to recover tracks in dense environments. Different variations, motivated by potential discrepancies between data and simulation, are performed to the neural network’s input while monitoring the corresponding change in the output. Within reasonable variation magnitudes, the neural networks prove to be robust to most variations.

In addition, a measurement of charged particle distributions is summarised. This is one of the first such measurements carried out for proton-proton collisions at $\sqrt{s} = 13$ TeV, limited to a phase space defined by transverse momentum $p_T > 100$ MeV and absolute pseudorapidity $|\eta| < 2.5$. Tracks are corrected for detector inefficiencies and unfolded to particle-level. The result is compared to the prediction of different models. Overall, the EPOS and PYTHIA 8 A2 models show the best agreement with the data.
Sammanfattning


Avhandlingen presenterar också en studie av distributioner av elektriskt laddade partiklar producerade i proton-proton-kollisioner. Det är en av de första studierna av partikeldistributioner för Large Hadron Colliders andra köring med masscentrum-energi $\sqrt{s} = 13$ TeV. Mätningen är begränsad till fasrymden definierad av en transversell rörelsemängd $p_T > 100$ MeV, och absolut rapiditet $|\eta| < 2.5$. Spår av partiklar rekonstrueras och korrigeras för detektorns ineffektivitet för att presenteras på partikelnivå. Dessa jämförs sedan med förutsägelser från olika modeller. Modellerna EPOS och PYTHIA 8 A2 är generellt de som bäst överensstämmer med data. Författaren har undersökt partiklar som migrerar in och ut ur fasrymden. Andelen spår associerade till partiklar som migrerat utifrån uppskattas med simulerad data, till som mest 10% nära fasrymdens gränser. Osäkerheten på denna andel uppskattas till att vara som mest 4.5%, huvudsakligen orsakad av osäkerheten på mängden material i de innersta subdetektorerna.
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Chapter 1

Introduction

The research carried out by ATLAS and the other experiments at the Large Hadron Collider at CERN concerns the fundamental question of what nature is made of. The Standard Model of particle physics has been hugely successful in describing nature’s building blocks. During the first run of the collider 2009–2012 the Higgs boson was discovered, confirming the postulated mechanism by which particles attain mass. Nonetheless, there are several phenomena and observations which the framework cannot account for. For example, it does not provide any satisfactory candidate particle to explain observations of so-called dark matter. The second run of the collider begun in 2015 and the research continues to validate the predictions of the Standard Model more precisely, as well as to search for new physical phenomena.

Despite passing extensive experimental tests throughout the last decades, there are certain interactions for which the predictions of the Standard Model are less accurate than in others. Being largely based on perturbation theory, the Standard Model can precisely predict interactions in which the strength of the coupling between particles is sufficiently small. When two protons meet inside ATLAS, most likely there will be a soft collision which is not involving a large momentum transfer between the colliding protons. Such soft collisions are difficult to model as the strong nuclear force has large strength at low momentum transfers; they take place in the non-perturbative regime. Dedicated phenomenological models must be used to predict these collisions. In Chap. 6 of this thesis, the analysis carried out by ATLAS at the start of the second run, measuring charged-particle distributions at proton-proton collisions with center-of-mass energy 13 TeV, is presented. This analysis study soft collisions in isolation and compares the data with predictions from different models. The analysis is also to a large extent experimentally motivated. The soft proton-proton collisions are almost always considered background, and must therefore be simulated as accurately as possible. This measurement provides useful insight into what model is best suited to simulate the soft collisions.

Proper reconstruction of charged-particle trajectories is paramount for most physics analyses carried out at ATLAS. Sophisticated software using pattern recognition is used to construct trajectories from the space point measurements provided
Chapter 1. Introduction

by the different inner detector subsystems in ATLAS. The innermost subsystem pro-
viding high resolution measurements is a silicon pixel detector. Chapter 5 outlines
a study of the robustness of the algorithm responsible for the forming of space point
measurements from clusters of neighbouring pixels. In environments where there
are several particles traveling through the detector as a narrow bundle, it happens
that multiple particles contribute to the same pixel cluster. Such environments are
common for example in searches for heavy resonances. To assure accurate recon-
struction also in dense environments the multi-particle clusters must be resolved as
often as possible. This is achieved with an artificial neural network algorithm, used
to estimate the number of particles contributing to a cluster. This algorithm is
trained on simulated data and relies heavily on accurate simulation of the detectors
response as well as an accurate charge calibration. The study probes the sensitiv-
ity of the neural network algorithm to uncertainties in the charge calibration or
differences between data and simulation. The changes are implemented as manual
variations and mainly concern the deposited amount and distribution of charge in
a cluster.

The thesis it outlined as follows. Chapter 2 contains a review of the Standard
Model. Chapter 3 explains the experimental facilities; the Large Hadron Collider
and the ATLAS detector. The way the detectors’ response is turned into recon-
structed physics objects is treated in Chap. 4. The pixel neural network robustness
studies are outlined in Chap. 5. Finally the study of charged-particle distributions
is presented in Chap. 6. The first three chapters are intended to be read in the order
in which they are presented, while the other two chapters are largely stand-alone.

1.1 Author’s contribution

The robustness studies presented in Chap. 5 are the authors qualification task
carried out during the first year in ATLAS. The work resulted in an internally
reviewed, publicly available note [1]. Chapter 5 is based heavily on this note. The
author is solely responsible for the work presented in this chapter.

The analysis measuring charged-particle distributions as presented in Chap. 6
was carried out by a working group of about 20 physicists. The analysis is sum-
marised in the author’s own words, using plots from the paper published in Physics
Letters B [2]. This is explicitly stated in the figure captions. The author was
responsible for estimating the systematic uncertainties on the number of charged
particles migrating in and out of the fiducial phase space. This contribution is
presented in Sec. 6.8, in which all plots and results are generated by the author.
Chapter 2

Theory and motivation

This chapter is primarily a compact review of the Standard Model of particle physics, and is based largely on references [3]. A short review of diffractive physics is given at the end.

2.1 The Standard Model

The current framework used in elementary particle physics is the Standard Model (SM) theory. It is a quantum field theory aiming at explaining all fundamental particles in the universe and their interactions. The exception is the gravitational interaction, which the SM by construction does not include.

The particle content in the standard model is shown in Fig. 2.1. These particles are elementary, meaning that they are to be considered point-like and have no substructure. The quarks and leptons make up the matter in the universe, and are spin-$1/2$ fermions. The gauge bosons have spin-1 and are so-called force carrier particles, mediating the strong and electroweak interactions. Lastly, there is the newly discovered Higgs boson, a spin-0 particle responsible for the generation of mass of the elementary particles through a symmetry-breaking process. The properties of the particles and the nature of their interactions is further outlined in Sec. 2.1.1.

While the SM is a hugely successful theory, it does have a number of shortcomings which are highlighted in Sec. 2.1.3.

2.1.1 Review of the elementary particles and their interactions

The visible matter content in the universe are the fermions which are further subdivided into leptons and quarks, as shown in Fig. 2.1. They are all spin-$1/2$ particles and each have a corresponding anti-particle, denoted with a bar. The leptons carry electric charge $-1$, the quarks $2/3$ or $-1/3$, while the neutrinos do not carry electric charge. There are three generations of quarks and leptons, corresponding to the
Figure 2.1. The particle content of the Standard Model. The three numbers in the top left corner of each square indicate the properties of the particle; the mass, electric charge and spin. In purple squares are the quarks, in green squares are the leptons, together comprising the matter particles. To the right are the gauge bosons in red, known as force carriers, and the Higgs boson in yellow. Image credit: Wikipedia user MissMJ, distributed under a CC-BY 3.0 license.
first three columns in Fig. 2.1. Each generation has its own lepton flavour quantum number associated to it. The masses of the particles differ by several orders of magnitude between the generations, but have otherwise the same properties.

The SM interactions have been observed to obey so-called gauge symmetries. In the language of group theory the SM may be formalised as the gauge group $G_{SM} = SU(2)_L \otimes U(1)_Y \otimes SU(3)_C$. The first two terms denotes the electroweak interaction, whereas the last term denotes the strong interaction. The electroweak interaction is mediated by the $W^\pm$ and $Z$ bosons and the photon. The weak gauge bosons, the $W^\pm$ and $Z$ particles, have masses 80.4 GeV and 91.2 GeV respectively, while the photon is massless. The electroweak interaction may be subdivided into the weak and the electromagnetic interaction, where the former denotes the one mediated by the $W^\pm$ and $Z$ particles and the latter the one mediated by the photon. Intrinsically, the weak and electromagnetic interaction are of the same strength, but the masses of the $W^\pm$ and $Z$ suppresses the weak interaction. This suppression is mostly pronounced in interactions involving momentum transfers of orders much smaller than the masses of the $W^\pm$ and $Z$. The $W^\pm$ and $Z$ couples to weak isospin, which is carried by all quarks and leptons. It is a special interaction in the sense that it is the only one that may change the lepton flavour of a quark or a lepton. Furthermore, only the left-handed components of particles take part in the weak interaction (hence the $L$ subscript in $SU(2)_L$). There are left-handed and right-handed particles, where the handedness denotes the chirality of the particle. Chirality is somewhat related to helicity, which is the projection of a particles angular momentum onto its direction of momentum. In the massless limit, chirality and helicity coincides, but the chirality is an intrinsic property whereas helicity is frame dependent. This makes the SM a chiral theory, in that it discriminates between the different chiral states.

The photon couples to electric charge, which is carried by all quarks and by the electron, muon and the tau particles. Since the photon is massless, the electromagnetic interaction has infinite range, while the massive $W^\pm$ and $Z$ bosons make the weak interaction short ranged.

The theory of the strong interaction is referred to as quantum chromodynamics (QCD). This interaction is mediated by gluons, which like the photons are spin-1 massless bosons. They couple to colour charge (hence the $C$ subscript in $SU(3)_C$), or in short colour, of which there are three, carried by both the quarks and the gluons themselves. There are eight different gluons, all carrying a colour-anticolour charge combination. The quarks (antiquarks) carry one unit of colour (anticolour). The fact that the gluons carry colour makes the strong interaction weaker at short distances, a phenomenon referred to as asymptotic freedom. No coloured particle, e.g. a quark or a gluon, have been directly observed. For example, quarks are only found together with other quarks in “colour-neutral”\(^1\) combinations called hadrons. The QCD potential contains a term proportional to $1/r$ and another term which increases linearly with distance. The strong interaction thus behaves like the electromagnetic interaction at short distances but grows linearly above distances

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\(^1\)I.e. colour singlets, invariant under $SU(3)$ rotations.
of order 1 fm. Due to the linear term in the potential, the energy stored in the
gluonic field between two coloured objects increases with distance. As two coloured
objects move apart, quark-antiquark pairs will eventually be formed at some cut-off
distance of order 1 fm. In effect, quarks are confined within hadrons. This means
that the strong interaction, in spite of having a massless mediator, effectively has
short range since coloured objects are never found further apart than $\sim 1$ fm. The
confinement property is believed to be due to gluon self-coupling (i.e. the fact the
gluons carry colour). Furthermore, this property is responsible for the formation
of jets, i.e. sprays of hadrons, as observed in hadron-colliding experiments like the
ones at the LHC.

The masses of the charged leptons are known to a high precision, while the
masses of the individual quarks are difficult to measure as they are confined within
hadrons. A large fraction of the mass of hadrons come from the binding energy
stored within them.

The Higgs sector of the SM was confirmed to exist relatively recently with
the observation of the Higgs boson in 2012 [4, 5]. The Higgs field is responsible
for generating the masses of the elementary particles. This is further detailed in
Sec. 2.1.2.

2.1.2 Spontaneous symmetry breaking and the
Brout-Englert-Higgs mechanism

The fact that the weak gauge bosons are massive indicates that the $G_{SM}$ is not a
symmetry of the vacuum. In the SM, the Brout-Englert-Higgs mechanism is re-
sponsible for a spontaneous breaking of the gauge symmetries associated with the
electroweak interaction. This leaves a broken $G_{SM}$ in a form which is a good sym-
metry of the vacuum. The Brout-Englert-Higgs (BEH) mechanism by which this
breaking is realised postulates a new Higgs field, with a non-zero vacuum expec-
tation value ($vev$). A perturbative expansion around this $vev$ effectively generates
the masses of the $W^{\pm}$ and $Z$ bosons, which evaluate to expressions proportional to
the $vev$. In addition, the masses of the fermions are generated through a Yukawa
coupling to the Higgs field, and are also proportional to the $vev$. Thus, masses in
the SM are generated through interactions with this non-zero $vev$ of the Higgs field.

The strength of the couplings to the Higgs boson (the quanta of the Higgs field)
for a particle is proportional to the mass of the particle, making the interaction
different from the other known interactions. In 2012 the ATLAS and CMS col-
laborations reported the discovery of a neutral scalar particle with a mass around
125 GeV, later confirmed to be a Higgs boson.
2.1.3 Short-comings of the Standard Model

The SM is an effective theory, describing the GeV regime very well.\textsuperscript{2} It is however not expected to be a complete theory valid at much higher energies like the Planck scale. Furthermore, the SM cannot explain a number of observed phenomena, and is considered to have inherent problems of theoretical nature. A selected number of these phenomena and problems, with some suggested solutions, will be described here.

The SM currently does not incorporate the force of gravity. Because of the vast discrepancy in relative strength between gravity and the other forces, gravity is not easily measured in a particle, small scale experiment. This is a problem for the theories aiming at merging quantum mechanics with gravity (so called quantum gravity models).

Many astrophysical observations suggest the existence of dark matter in and around galaxies, matter that does not interact electromagnetically and thus is not visible (see e.g. Ref.[6]). The nature of this dark matter is unknown and many searches are performed in different experiments. There are the direct detection experiments, targeting dark matter particle interactions with a dedicated detector. There are indirect detection experiments, such as telescopes, measuring astrophysical particles to infer annihilation of dark matter particles. Lastly, collider experiments aim at producing dark matter particles and infer its existence from the signature left in the detector (e.g. the ATLAS detector).

The so-called hierarchy problem is a theoretical problem and concerns the apparent smallness of the vacuum expectation value of the Higgs field. Consider for example the Higgs boson mass, to which radiative corrections (i.e. loop diagrams) from other fields contribute. Some contributions will be much larger than the electroweak scale, e.g. contributions from gravity which will become significant at the Planck scale. Because of the large differences in scale, the SM in its current state must contain extremely fine-tuned cancellations of these contributions to agree with the observed Higgs boson mass at the electroweak scale. This is by many considered an undesired feature of the model, and so many theories and have been put forward to solve this problem in a more “natural” way. Perhaps the most popular class of such theories are supersymmetric models. These models postulates a new symmetry between fermions and bosons. This predicts supersymmetric partners for all the particles in the SM. So far, no such supersymmetric particles have been observed, but the topic remains interesting and searches continue during run 2 of the LHC.

In the SM, neutrinos are massless. This is in obvious contradiction with the observation of neutrino lepton flavour oscillations, as was awarded the Nobel prize in physics 2015. The exact mechanism through which they acquire mass is not known, neither are their absolute mass values. The latter may be constrained by a combination of cosmological measurements, oscillation experiments and direct detection experiments.

\textsuperscript{2}The analogy may be done with Newton’s laws of motion, which are valid provided that the involved objects are not too small and moving with non-relativistic speeds.
2.2 Diffractive physics and the pomeron

The total $pp$ cross section at the LHC is dominated by collisions with low momentum transfer which cannot be predicted with perturbative QCD. The total cross section and the cross section for typically interesting processes is shown in Fig. 2.2, while the breakdown of the total cross section in its elastic and inelastic parts is shown in Fig. 2.2. In elastic hadron collisions a diffraction pattern is observed for the outgoing particles. Hence the term “diffraction” is often used in association with elastic collisions, however, the word has later also come to include a specific class of inelastic collisions. So-called diffractive events denote collisions in which there is no exchange of colour charge between the colliding particles. In such events the colliding particles may (inelastic) or may not (elastic) be broken up. As there is no colour exchange in diffractive events, they produce special topologies characterised by rapidity gaps. The colour singlet exchange is usually referred to as a “pomeron”, the exact nature of which is not known. It was introduced as a special kind of Regge trajectory – the exchanged particle in Regge theory\(^3\) – which could explain the rise in $pp$ cross section with $\sqrt{s}$ (see Fig. 2.2). At the HERA electron-proton collider diffractive topologies were probed by the L1 and ZEUS experiments \([7, 8]\). Fits to this data allow for an interpretation of the content of the pomeron in terms of a quark-gluon QCD picture. Such fits suggest that the pomeron is gluon dominated \([9]\).

As perturbative QCD may not be used to calculate pomeron-based cross sections, different phenomenological models have been developed. They are QCD inspired and typically contain parameters which require to be tuned to experimental data. In particular, charged particle distributions are useful for this purpose. Such measurements have been performed by ATLAS for $\sqrt{s} = 13$ TeV and is explained in detail in chapter 6.

\(^3\)Regge theory is one of the theories commonly used prior to the discovery of the quarks and gluons and the birth of QCD.
2.2. Diffractive physics and the pomeron

Figure 2.2. The total $pp$ cross section and the cross section of some typically interesting physics processes. Figure reference: W.J. Stirling, private communication.
Figure 2.3. The total $pp$ cross section and its breakdown in inelastic and elastic parts. The different data points are from different experiments. Figure from Ref. [10].
Chapter 3

Experimental facilities

This chapter contains a review of the experimental facilities, i.e. the Large Hadron Collider (LHC) and the ATLAS detector with its subsystems.

3.1 The Large Hadron Collider

The LHC is a circular accelerator located in a tunnel roughly 100 m underground, on the border between Switzerland and France near the CERN site. It accelerates protons and heavy ions up to centre-of-mass energies of $\sqrt{s} = 13 \text{ TeV}$\(^1\) and $\sqrt{s} = 2.8 \text{ TeV}$ per nucleon respectively, before they are made to collide at the different experiments situated along the ring. In what follows, the proton-proton collisions will be described, as these are the main focus of the ATLAS experiment. The protons are extracted from hydrogen and accelerated in steps in different accelerators, with the LHC being the final one. First, the protons enter the linear accelerator Linac2 and are brought up to an energy of 50 MeV. They are then accelerated by circular accelerators; first the Booster, then the Proton Synchrotron (PS) and finally the Super Proton Synchrotron (SPS) before being injected into the LHC. The energies acquired at the different accelerator are 1.4 GeV, 25 GeV and 450 GeV respectively. It is the PS that sets the bunch spacing to 25 ns. Inside the LHC, the protons are accelerated up to 6.5 TeV per beam using radio-frequency (RF) cavities.

Along the LHC ring, there are 1232 super-conducting NbTi dipole magnets bending the protons, keeping them in orbit. Liquid helium cooling provides an operating temperature of 1.9 K, enabling a current of 11 kA which generates an 8 T dipole field. Furthermore, 392 quadrupole magnets are responsible for focusing the proton beams.

Down the accelerating chain towards the LHC, the circumference of the different accelerators increases. Therefore, to fill an accelerator with proton bunches, several fills of its preceding accelerator are injected. The exact scheme in which the different

\(^1\)The design energy of LHC is $\sqrt{s} = 14 \text{ TeV}$, however it is currently operated at $\sqrt{s} = 13 \text{ TeV}$.\)
accelerators are sequentially filled with proton bunches effectively determines the bunch pattern as finally obtained in the LHC. When the PS is filled it holds 72 proton bunches and 12 empty bunches. Next, an SPS fill consists of two, three or four PS fills. Finally, the LHC consists of 12 of these variable-length SPS fills, holding up to 3564 proton bunches per beam. See Fig. 3.2 for a schematic view of how the different accelerator fills are composed. There are different “distances” in time, i.e. number of empty bunches, between the different types of fills. It is important to keep a 3 μs gap in the LHC filling scheme, a so-called abort gap. This time gap is needed for the kicker magnets to ramp up and divert the protons and dump the beam.

The RF cavities provide an oscillating longitudinal electric field, accelerating the protons from 450 GeV to 6.5 TeV. The field oscillates at a frequency of 400 MHz; an integer of the bunch passing frequency 40 MHz. This assures the protons experience an accelerating field only inside the cavity. This design causes the bunches to stay compact as they will tend toward certain positions along the circumference as determined by the oscillation frequency. This allows for high luminosity when the beams are collided at the experiments.

The luminosity of a collider is a measure of the number of protons crossing each other per unit time and area. The figure characterises the intensity, or brightness, of the collider, and predicts together with the proton-proton cross section the average rate of proton-proton collisions to be expected. It is given by the following expression [13]

$$L = \frac{N_p^2 n_b f \gamma}{4\pi\epsilon \beta^* F}, \quad (3.1)$$
3.2 The ATLAS detector

The ATLAS detector, see Fig. 3.3, is a huge assembly of experimental equipment, weighing some 7000 tonnes and measuring 44 m in length and 25 m in height. It is a cylindrical magnetic spectrometer with forward-backward symmetry, designed

\[ \text{where } N_p \text{ is the number of protons per bunch, } n_b \text{ the number of bunches in one beam, } f \text{ the revolution frequency, } \gamma \text{ the Lorentz factor, } \epsilon \text{ the normalised transverse beam emittance, } \beta^* \text{ the beta function at the collision point and } F \text{ a geometrical factor correcting for the beam-beam crossing angle. The numerator of this expression equals the number of protons crossing each other per unit time, whereas the denominator terms equals the area over which the protons are distributed during collision. The design luminosity of the LHC is } 10^{34} \text{ cm}^{-2}\text{s}^{-1}, \text{ a merit that was almost reached during run 1 which recorded a peak luminosity of nearly } 8 \cdot 10^{33} \text{ cm}^{-2}\text{s}^{-1}. \text{ If the luminosity is integrated over time, a measure of the total amount of collisions produced is obtained. This number may be multiplied with the cross section for a physical process to infer the expected number of events from that process to be found in the full dataset.} \]

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Chapter 3. Experimental facilities

as a multi-purpose detector. The different subsystems will be described in this section, which is largely based on Ref. [14].

![Figure 3.3. A cut-away view of the ATLAS detector. Credit: CERN](image)

### 3.2.1 The inner detector

The inner detector provides measurements of charged particles, used to reconstruct their trajectories (see Sec. 4.1). Charged particles traversing the inner detector are bent by a 2 T axial magnetic field provided by a superconducting solenoid magnet, allowing for momentum measurement from the curvature of the track. The inner detector consists of silicon pixel and microstrip detectors and a transition radiation tracker. It is depicted with its subsystem in Fig. 3.4. As up to 1000 charged particles may be produced in a collision, the requirements put on precision and performance of this system are strict. In the following three sections the three subsystems will be described, with an emphasis on the pixel detector as it is important for the studies presented in this thesis.

**The pixel detector**

The pixel detector is a high-granularity silicon detector, segmented in \( z \) and \( R - \phi \). It consists of four cylindrical layers in the central region and three disks at each end-cap in the forward regions. The innermost layer is positioned at \( R = 3.5 \) cm, the outermost layer at \( R = 12.2 \) cm. In total, the detector comprises 1968 sensors used in the transverse plane, \( \phi \) being the azimuthal angle around the \( z \)-axis. The pseudorapidity is defined in terms of the polar angle \( \theta \) as \( \eta = -\ln \tan(\theta/2) \).
3.2. The ATLAS detector

Figure 3.4. An overview of the ATLAS inner detector and its subsystems. Figure (a) is showing the different subsystems’ location and the overall ID dimensions, Figure (b) is showing the radial placement of the different layers in the barrel region. Image credit: CERN.

and some 80 million readout channels. The position of a measurement in the pixel detector is given in the local coordinate frame, with the local $x$ and $y$ directions for the barrel modules approximately coinciding with the global $R−\phi$ and $z$ directions, respectively.

The innermost pixel layer (IBL) was inserted for run 2 of the LHC. By providing an additional measurement closer to the interaction point, it increases the impact parameter resolution of reconstructed tracks\(^3\). Furthermore, the IBL is required to maintain track reconstruction performance as the performance provided by the other pixel layers alone decreases with increased radiation dose. The pixel dimensions in the IBL are $50 \times 250 \ \mu m$ in the local $x$ and $y$ directions respectively, and $50 \times 600 \ \mu m$ in the other three layers. About 10% of the pixels have longer pitches in the local $y$ direction, namely 400 $\mu m$ in the IBL and 600 $\mu m$ in the other three layers. The pixels with longer pitches are located at the edge between modules. The thickness of the silicon sensors are 200 $\mu m$ for the IBL and 250 $\mu m$ for the remainder of the pixel detector.

The pixel detector provides a measurement of the charge deposited, corresponding to the energy lost by a particle traversing a silicon sensor. The charge deposited in the detector is collected and amplified by a preamplifier in the front-end chip. Only pixels above a predefined threshold are read out. The recorded time-over-threshold (ToT), i.e. the period of time during which the preamplifier output signal

\(^3\)The impact parameter is the point of closest approach between a track and its associated vertex. See Sec. 4.1 for a review of the charged particle reconstruction.
is above this predefined threshold, increases approximately linearly with the deposited charge. The signal is digitised in clock cycles of the readout chip and converted to a charge value at the cluster reconstruction stage using parametrisations derived from calibration data.

The IBL has 4-bit pixel readout, whereas the remainder of the pixel detector has 8-bit pixel readout. The IBL pixel readout saturates at a ToT value of 15 clock cycles, in contrast to the 8-bit readout, saturating at a value of 255 clock cycles.\footnote{In practice, for the 8-bit readout, this saturation level is seldom reached.} To obtain a uniform response for all pixels, the ToT is tuned such that the average ToT for a charge deposition close to that deposited by a minimum ionising particle is the same for all pixels. A charge deposition of 16 000 (20 000) electrons was tuned to 10 (30) clock cycles for the IBL (the remainder of the pixel detector). The different charge depositions in the IBL and the remainder of the pixel detector are motivated by the different silicon sensor thicknesses.

The SCT detector

Moving radially outwards we find the semiconductor tracker (SCT), which like the pixel detector is based on silicon technology. It consists of silicon micro-strip sensors mounted on four cylindrical layers in the barrel region and nine disks at each end-cap. Strips are mounted on both sides of the sensors with an 80 $\mu$m pitch and a 40 mrad stereo angle, running approximately longitudinally (radially) in the barrel (end cap) region. A stereo angle size of $\pi/2$ radians is not optimal due to the high expected occupancy. A space point is built from two strip measurements, one from each side of the sensor. The total number of SCT channels is around six million. In contrast to the other two subsystems the SCT has digital read-out; it does not provide any information about the energy deposited.

The TRT

Furthest out in the tracking system is the Transition Radiation Tracker (TRT) which deploys a classical technique for detecting charged particles. It consists of straw tubes filled with a Xe-based gas mixture which is ionised when traversed by charged particles. A voltage causes the freed electrons to drift towards a gold-plated tungsten anode wire in the middle of the tube. The acceleration causes further ionisation to take place near the wire and an avalanche of electrons develops. The electrons are collected on the wire and read out as a signal. The TRT typically supplies some 35 measurements, with roughly 130 $\mu$m resolution in the $R - \phi$ plane but practically no information about the $z$ (straw) direction. The straws are interleaved with a plastic material designed to induce transition radiation. When a charged particle crosses a surface between two materials with different dielectric constants, it has a certain probability to emit transition radiation. The amount radiation produced is proportional to the particle’s Lorentz boost factor $E/m$. The transition radiation photons induce further ionisation signals, allowing
for discrimination between the relatively lighter electrons with a high Lorentz boost and heavier charged hadrons such as pions.

### 3.2.2 Calorimetry

As implied by the name, the task of the calorimeters is to measure energy. ATLAS has five calorimeter systems which may be divided into two categories; one electromagnetic (EM) category and one hadronic category, as shown in Fig. 3.5. The EM calorimeter is designed to fully contain the showers produced by electrons and photons, whereas hadrons will deposit some energy in the EM calorimeter but not be fully stopped until in the hadronic calorimeter. Both systems are so-called *sampling calorimeters* in which absorbers, initiating showers, are interleaved with active material measuring the showers. In this section, the five calorimeters subsystems will be described within their respective category.

![Figure 3.5. An overview of the ATLAS calorimeter system. Image credit: CERN.](image)

**The electromagnetic calorimeter**

The EM calorimeter consist of one barrel and two end cap parts. They all use liquid argon (LAr) as active material and lead as absorber material. The lead is structured in an accordion shape, symmetrical around the $z$ axis, with liquid argon filling the gaps in between. A wedge of the EM barrel calorimeter is shown in Fig. 3.6, displaying its three layers with differing cell granularities. The first layer

---

5This is in contrast to homogenous calorimeters in which a single material act both as absorbers and active material.
has fine segmentation in $\eta$, allowing for discrimination between prompt photons and photons from $\pi^0$ decays. The accordion structure allows for full $\phi$ coverage without cracks, while simultaneously assuring that particles pass through roughly the same amount of material across the $\phi$ range. As bremsstrahlung and pair production both are proportional to the square of the atomic number $Z$ of the nearby nucleus, the particle showering will typically be initiated and predominantly develop in the lead. The showers will ionise the liquid argon, where the liberated electrons will drift due to an applied electric field and be read out as a signal. The resolution in the energy measured for the EM calorimeter is approximately

$$\frac{\sigma}{E} \sim \frac{10\%}{\sqrt{E[\text{GeV}]} \oplus 0.7\%},$$

(3.2)

where the energy dependent term arises from statistical fluctuations in the showering and the constant term arises from imperfections.

The choice of liquid argon as active material is motivated by requirements on linearity, stability and ability to withstand high radiation doses.

**Figure 3.6.** A wedge of the EM barrel calorimeter. The calorimeter consists of lead absorbers arranged in an accordion structure with liquid argon as active material between the lead plates. There are three layers with different cell size. Image taken from Ref. [14].
The hadronic calorimeter

The hadronic calorimeter is located directly outside the EM calorimeters and consist of the Tile central barrel, the Tile extended barrel and the hadronic LAr end caps. The Tile calorimeters have iron as absorber material and plastic scintillators as active material. They are paramount to ensure proper identification and measurement of hadronic jets. The Tile Calorimeters are equipped with photo multiplier tubes to measure the light emitted from the scintillators. The hadronic calorimeters have an approximate energy resolution

\[
\frac{\sigma}{E} \sim \frac{50\%}{\sqrt{E[\text{GeV}]}} \oplus 3\%,
\]

(3.3)

The hadronic LAr end caps are similar to the LAr electromagnetic end caps but has copper as absorber material.

The forward calorimeter

In the forward region, covering \(3.1 < |\eta| < 4.9\), is the LAr based forward calorimeter. It consists of three layers per end cap. The first is made of copper, optimised for electromagnetic showers. The other two are made of tungsten, designed to measure hadronic showers. The detector front face is situated 1.2 m further out with respect to the electromagnetic calorimeter end cap front face, to reduce the neutron albedo in the inner detector cavity. This limits the depth of the detector and it therefore has a high-density design. The forward calorimeter depth amounts to approximately 10 interaction lengths.

3.2.3 Muon system

Muons are the most elusive charged particles to be measured by ATLAS as they typically penetrate the inner detector and the calorimeters. To reach the muon system, depicted in Fig. 3.7, a muon must have a momentum of more than approximately 3 GeV. This is the largest and the outermost subsystem reaching from approximately \(R = 5\) m to \(R = 11\) m. It is a spectrometer with its core piece being the magnet system causing the muons to bend and allow for momentum measurement. There are three superconducting toroids, each with eight coils; one in the barrel region and one for each end-cap. The magnetic field has a complicated structure and is mapped by magnetic field sensors to a precision of 0.1 mT. The complexity of the field requires a detailed numerical approximation track model rather than an analytical expression.

The momentum measurements are provided by high-precision tracking chambers, covering \(|\eta| < 2.7\), while dedicated trigger chambers provide fast measurements in \(|\eta| < 2.4\). The chambers are mounted as three cylindrical layers in the barrel region at radii \(R = 5\) m, \(R = 7.5\) m and \(R = 10\) m. In the forward regions there are four wheels on each side at distances 7.4 m, 10.8 m, 14 m and 21.5 m mounted with chambers. This design provides at least three measurements for a
muon passing through the muon system, allowing for the radius of curvature to be measured. The $p_T$ resolution of the muon system is best, $\sim 3\%$, at $p_T = 100$ GeV. Above (below) this transverse momentum the resolution decreases to approximately $\sim 10\%$ ($6\%$) at 1000 GeV (4 GeV). It decreases below $p_T = 100$ GeV due to fluctuations in the amount of deposited energy in the material downstream of the muon system. The amount of material between the interaction point and the muon system varies between 100 and 190 radiation lengths depending on pseudorapidity, and consists mostly of calorimeters. A description of the different chambers will now follow.

**Monitored drift tube chambers**

The monitored drift tube chambers (MDTs) covers $|\eta| < 2.0$ and are used for precision tracking and based on the same classical technology as the TRT. MDT’s are located both in the barrel and in the end-caps. The have aluminium tubes of diameter $\sim 30$ mm filled with an Ar-CO$_2$ gas mixture, and a tungsten wire inside. The tubes are arranged in multi-layers and a muon typically passes through 20 individual tubes on average. The alignment of the MDTs has to be known to a high precision, for which a system of approximately 12000 optical sensors are used to map the sensors’ internal deformations and relative positions.
3.2. The ATLAS detector

Cathode strip chambers

In the forward region $|\eta| > 2$ the particle flux is higher than what the MDTs can handle in terms of safe operating counting rate per unit area. To cope the muon system is equipped with cathode strip chambers (CSCs) in the region $2.0 < |\eta| < 2.7$, in the end-caps. There are $2 \times 8$ chambers per end-cap; eight small and eight large chambers on two disks. These are multi-wire proportional chambers with anode wires in the radial direction. As ionisation electrons from the Ar-CO$_2$ gas mixture collect on the wires currents are induced in the cathodes, which are read out (the wire current is not read out). The cathodes are segmented into strips; one with strips oriented in a direction perpendicular to the wire, the other with strips oriented parallel to the wire. This allows for measurement of the charge distribution in both directions perpendicular to the beam line, yielding a resolution of approximately 60 $\mu$m (to be compared with 80 $\mu$m for the MDTs).

Trigger chambers

The muon trigger system provides fast measurement of muon $p_T$, as well as bunch crossing identification and discrimination against background. In the barrel region ($|\eta| < 1.05$) are the RPCs, in the forward region ($1.05 < |\eta| < 2.4$) are the TGCs. There are three cylindrical layers of RPCs, each with one RPC layer at each end-cap. The RPCs consist of resistive plates with gas in between, the latter being ionised upon a muon traversing. An electron avalanche is built up due to a voltage applied across the plates, which is read out. The TGCs are based on multi-wire proportional technology like the CSCs, and provide finer $\eta$ granularity than the RPCs. This assures the same $p_T$ resolution in the barrel region; the particle momentum increases with $|\eta|$ for a fixed $p_T$, meaning there is less bending power in the forward region.

3.2.4 Trigger and data acquisition

The LHC bunch crossing rate corresponds to a 40 MHz rate of events. Recording all those events would require many terabytes of data to be written to disk every second, which is unfeasible. Furthermore, only a fraction of the events will contain interesting physics. To cope with this, ATLAS has a dedicated trigger and data acquisition (TDAQ) system [15], which is designed to reduce the final read-out rate to order 1 kHz. This limit is imposed by the amount of data ATLAS may store. The TDAQ must make a fast decision as to whether an event is worth recording, or not. If an event is discarded by the TDAQ, it is permanently lost.

The trigger chain system consists of two main levels: the first level-1 (L1) and the second high-level-trigger (HLT). The L1 system is hardware based, as it needs to be extremely fast. It uses low-granularity information from dedicated calorimeter and muon trigger detector subsystems to find high-$p_T$ objects, namely muons, electrons, photons, jets and hadronically decaying tau leptons. No inner detector information is used at this stage, to reduce the event size. The L1 trigger system needs to reduce the rate to 75 kHz, a limit set by the front-end electronics ability to process
information. This is the main limiting factor on the whole TDAQ system, imposed by the speed at which the detector signals may be transferred. To achieve this, the L1 is designed to reach a verdict within 2.5 $\mu$s.

So-called Regions-of-Interest (RoI) are passed on to the next, software based HLT system. They are $\eta$–$\phi$ regions in which interesting activity have been detected. In the first step of the HLT, full-granularity information is read out in the RoIs, now including the inner detector track information allowing for matching of calorimeter deposits and tracks. Based on this information the event may be rejected or not. If not rejected, the second step of the HLT follows. The full event information is read out and event building is performed, giving a simplified but full event picture. This allows for using offline reconstruction algorithms to finally decide whether to accept the event or not.

At different levels in the TDAQ pre-scales may be applied to the data. A pre-scale is a number determining the fraction of events to keep from a trigger selection. For example, a pre-scale of five implies that only every fifth event surviving a trigger selection will actually be kept and further processed. This means that events coming from a stream with pre-scaled triggers will effectively be associated with a lower luminosity than the baseline one. Analyses must take this into account, and thus tend to use un-prescaled triggers as much as possible.

Events selected by the TDAQ are sent to full reconstruction at the on-site processing centre known as Tier-0. Once fully reconstructed, the data is distributed world-wide to different computing centres, then available for analysis.
Chapter 4

Particle Identification

As particles produced in the $pp$ collisions traverse the ATLAS detector they interact with the different subsystems by depositing energy in them (see Sec. 3.2). This produces raw electrical signals, which are digitised and read out to be used in the event reconstruction. This information must be processed in the appropriate way to form the physics objects which are needed for the physics analyses, such as electrons and muons. This often requires using signals from different subsystems. The detector is designed so as to deliver a unique signature for each class of particles. For example, all charged particles are expected to leave a track in the inner detector. The magnetic field will cause the particles to bend in a direction depending on the sign of the charge. This allows for reconstructing electrons by combining showers in the electromagnetic calorimeter with a track in the inner detector. For photons, no inner detector track is expected, and as compared to electrons a slightly different shower shape is expected in the electromagnetic calorimeter. Hadrons are expected to leave a small fraction of their energy in the electromagnetic calorimeter and most of their energy in the hadronic calorimeter. The association of an inner detector track allows for discrimination between e.g. protons and neutrons. Collimated sprays of hadrons may be grouped together and be reconstructed as jets. Muons are expected to leave a signal in all the different subsystems of detector and thus information from all of them are combined. Lastly, some particles (like neutrinos) will go undetected and will thus leave an imbalance of momentum and energy in the transverse plane (the $x$-$y$ plane; perpendicular to the beam direction). Thus, the missing transverse momentum in an event may be reconstructed by taking the negative sum of the reconstructed physics objects visible in the event. A sketch of the typical corresponding signals left in the ATLAS detector by different particles are shown in Fig. 4.1, indicating the identification capabilities.

In this chapter, the algorithms used to reconstruct some of the most important physics objects will be outlined.
Chapter 4. Particle Identification

Figure 4.1. A sketch of the typical signatures left by different particles in the ATLAS detector, seen in the transverse plane. By combining information from the different detector subsystems, particles may be identified and distinguished from each other. Image credit: The ATLAS experiment.
4.1 Charged particle reconstruction

Charged particles are reconstructed as tracks using measurements from the ATLAS inner detectors. The ATLAS track reconstruction algorithm [16] realises an inside-out strategy primarily and a complementary outside-in strategy. Here the inside-out strategy will be outlined.

A staged pattern recognition approach is used to first find a set of loose track candidates seeded on combinations of three measurements from the silicon detector layers. Each measurement must come from a unique layer. The IBL and the pixel detector provides clusters, formed from neighbouring\(^1\) pixels grouped together. These measurements map directly into three-dimensional space-points. For the SCT, space-points are formed by combining measurements from pairs of measurements from two strips on a SCT module. There are four possible combinations of space points to make up a seed: all space-points in the pixel detector or all in the SCT, two space-points in the pixel detector and one in the SCT or one space point in the pixel detector and two in the SCT. The fourth category is not used by the seeding algorithm. Using three space points to form a seed maximises the number of combinations while still enabling for a first crude estimate of the momentum. The track parameters are estimated assuming a perfect helical trajectory and uniform magnetic field, with respect to the center of the interaction region. To maximise purity a number of quality cuts are put on the seeds, such as a minimum momentum and a maximum impact parameter requirement\(^2\). Also, usage of the same space points in multiple seeds is carefully controlled, and a fast check is performed to validate that a fourth space point is compatible with the seed.

The track candidates are built from the seeds using a combinatorial Kalman filter [17]. A window search is performed to add to the track candidate additional space points from measurements expected in the remaining layers. The road within which to search is estimated from the propagated track seed parameters. Space points found within the road may be added to the track candidate if they are compatible with the track candidate in its current state. If a space point is successfully added to the track candidate, the track parameters are updated with the new information and then used in the next filter iteration. If multiple space points on the same layer are compatible with the track candidate, multiple track candidates are formed and proceed independently in the subsequent filtering. Each iteration in the filtering takes into account particle-matter interactions and movement through the magnetic field.

Once the set of track candidates is complete, it is the job of the ambiguity solver stage to further filter out tracks which have incorrect space point assignment. The ambiguity solver compares and rates individual tracks based on their quality. Each track is assigned a relative score and tracks with low score are discarded at this stage. The track scoring scheme is based mainly on basic track quality

\(^1\)Sharing at least one corner.

\(^2\)The impact parameter is defined as the distance of closest approach between the track and a reference point, typically the primary vertex.
measures. For example, holes\(^3\) get penalised, while a good track fit $\chi^2$ increases the score. Finally, the tracks surviving the ambiguity solver stage are extended to the TRT. The TRT extension is also performed with a Kalman filtering approach, searching for additional compatible space point measurements to be added to the track. The silicon detector tracks surviving the ambiguity solver stage define the search window.

### 4.2 Electrons and photons

Electron and photon reconstruction both uses information from the electromagnetic calorimeter. Calorimeter clusters of cells are seeded on groups of neighbouring cells found by a so-called “sliding window” algorithm searching for local $E_T$ maxima. The size of the clusters have been optimised to have a high efficiency of reconstructing a typical electromagnetic shower, while at the same time keeping the level of noise contribution low.

For electrons, clusters are then matched to inner detector tracks. A track is required to be consistent with the cluster both in position and in momentum. A multi-variate likelihood is finally built from different shower property variables, track-to-cluster variables and track quality measures. Depending on the value of the likelihood, the algorithm classifies the electron as satisfying either loose, medium or tight identification criteria. By a tighter category is implied a higher purity, but a lower efficiency.

Photon-induced showers are very similar to electron-induced showers, but a few discriminant variables exist and are used to distinguish electrons from photons to some degree. More importantly though, the shower is required not to have an associated track. Photons interacting with material in e.g. the beam pipe may convert to an electron-positron pair, giving rise to both inner detector tracks and an electromagnetic cluster, mimicking the signature of an electron or a positron. Such conversion pairs may be identified by matching the calorimeter cluster to a pair of inner detector tracks.

### 4.3 Muons

Muons are reconstructed with information from mainly the muon system and the inner detector, and to a lesser extent calorimeter data. Information from the different subsystems may be combined in different ways, leading to four types of muons: Combined muons, formed from a track in the muon system matched to a track in the inner detector; Extrapolated muons, formed from only a track in the muon system and a loose requirement on the compatibility with originating from the interaction point; Segment-Tagged muons, formed from an inner detector track matched to at least one local track segment in the muon system; and Calorimeter-Tagged muons.

\(^3\)A hole is the absence of a measurement in the region where one is expected (the intersect between the detector and the track).
formed from an inner detector track matched to calorimeter data compatible with coming from a minimum ionising particle. The Extrapolated muons are mainly used to extend the region of acceptance to $2.5 < |\eta| < 2.7$, which is outside the range of the inner detector. Overlap between different types are resolved before the reconstructed muons enter in to physics analyses. When two muons share the same inner detector track, preference is given to Combined muons, followed by Segment-Tagged muons and then Calorimeter-Tagged muons. When two muons share the same muon system track, preference is given to the track with better track quality.

Muon identification aims at reconstructing muons at high efficiency while keeping the rate of fakes, coming mainly from kaons and pions decaying in-flight, low. Similarly to electron identification, there are loose, medium, tight and high-\(p_T\) selection criteria. The different criteria applies a set of quality cuts based on the specific features of the muon type, as listed above. The loose identification criteria is optimised for reconstructing the four-lepton final state of Higgs boson candidate events and has a high reconstruction efficiency, using all muon types. The medium identification criteria uses only Extrapolated and Combined muons and is the default muon selection in ATLAS. Depending on the type, requirements on the number of hits in the different muon subsystems are applied, together with a very loose compatibility requirement between the muon system track and the inner detector track for the Combined muons. The tight identification criteria is designed to have a high purity and consists only of Combined muons satisfying the medium criteria with additional quality cuts. Finally, the high-\(p_T\) selection maximises the momentum resolution for muons with \(p_T > 100\) GeV, using Combined muons satisfying the medium identification criteria and applying additional muon system hit requirements [18]. The loose and medium muons have very similar reconstruction efficiency and is above 98% (except in a muon system gap at $|\eta| < 0.1$) for muons with $p_T > 10$ GeV. Tight muons have a reconstruction efficiency between 90% and 98%. All efficiencies are in good agreement with those predicted by simulation.

### 4.4 Jets

A jet is a spray of hadrons, a commonly emerging product at hadron colliders. The reconstruction of jets begins with forming topological calorimeter clusters, or topo-clusters. Topo-clusters are seeded on calorimeter cells with a signal-to-background-ratio ($S/B$) larger than four. The $B$ in this ratio includes expected activity from pile-up interactions and is thus robust against different pile-up conditions. Neighbouring cells are iteratively added to the cluster if they fulfil $S/B > 2$. Finally, ternary neighbours with $S/B < 2$ are also added to the cluster, but the iteration procedure stops here. From the collection of resulting topo-clusters, two topo-clusters are split if found to be compatible with being overlapping. Due to the sampling nature of the ATLAS calorimeters, the clusters are then calibrated on a cell-by-cell basis using EM and hadronic calorimeter data. At this stage, the topo-clusters are input to the jet finding algorithm.
There are many jet finding algorithms on the market, each with its advantages and disadvantages. A desirable feature of a jet algorithm is to be infrared safe, meaning that it is robust against soft and collinear radiation. The first step in combining the calibrated topo-clusters, i.e. jet constituents, is to define the $k_t$ distance measures

$$
\begin{align*}
  d_{ij} &= \min(k_{t,i}^{2p}, k_{t,j}^{2p}) \Delta_{ij}, \\
  d_{iB} &= k_{t,i}^{2p}
\end{align*}
$$

where $\Delta_{ij} \equiv (y_i - y_j)^2 + (\phi_i - \phi_j)^2$ and $k_{t,i}$, $y_i$ and $\phi_i$ is the transverse momentum, rapidity and azimuthal angle of constituent $i$, and $d_{iB}$ is the $k_t$ distance between constituent $i$ and the beam. $R$ and $p$ are parameters denoting the “radius” (a measure of the size of the jet) and the relative power of energy versus size, respectively. Starting with constituent $i$ and considering all $k_t$ distances to other constituents, $i$ and $j$ are combined into a new constituent if $d_{ij} < d_{iB}$. This process is repeated until no other constituent can be added and the resulting object is then considered a jet and all its constituents removed from the list of possible constituents for additional jets.

If $p = -1$ the so-called anti-$k_t$ algorithm is obtained [19], commonly used in ATLAS. Jets reconstructed with the anti-$k_t$ algorithm are infrared safe. The algorithm is designed so as to let the harder constituents determine the general characteristics of the jet. Softer constituents will tend to cluster with the harder constituents before with clustering among themselves. The resulting jets are in general conical in shape with radius equal to $R$. If two hard constituents have $\Delta_{ij} \sim R$ the shapes might divert slightly from the conical shape, but always favouring the harder constituent.

The different properties of quarks are utilised to discriminate between jets originating from $b$ quarks and jets originating light ($u,d,s$) quarks. In particular, the lifetime of the $b$ quark is relatively long, resulting in $B$ hadrons with a lifetime of the order 1.5 ps. The average decay length of such hadrons is a few millimetres, long enough to reconstruct a secondary vertex from the decay products. Furthermore, as the decay of quarks is mediated by the weak interaction, soft leptons can be produced in the decay chain. The algorithms developed to classify jets as originating from $b$ quarks are multivariate and mainly exploit track information and reconstructed secondary vertices. The impact parameter of tracks associated to a $b$-jet will tend to be larger than the impact parameter of corresponding light-jet tracks which are associated to the primary vertex. Efficient $b$-tagging is important in particular for analyses involving the top quark, as it decays to a $b$ quark.

4.5 Missing transverse momentum

The ATLAS detector is designed to infer the existence of particles traversing the whole detector without leaving a trace, such as neutrinos or particles in beyond-the-Standard-Model (BSM) theories. This is possible through the detection of an
imbalance in momentum in the transverse plane. The *missing transverse momentum* of an event, $E_T^{\text{miss}}$, is defined as the negative sum of the transverse momentum of all the other visible objects. It is computed as

$$|E_T^{\text{miss}}| = \sqrt{(E_x^{\text{miss}})^2 + (E_y^{\text{miss}})^2}, \quad \phi^{\text{miss}} = \arctan\left(\frac{E_y^{\text{miss}}}{E_x^{\text{miss}}}ight)$$

where

$$E_x^{\text{miss}} = E_x^{\text{miss}, e} + E_x^{\text{miss}, \gamma} + E_x^{\text{miss}, \tau} + E_x^{\text{miss}, \text{jets}} + E_x^{\text{miss}, \mu} + E_x^{\text{miss}, \text{soft}}.$$  \hspace{1cm} (4.2)

The $e, \gamma, \tau, \text{jets}$ and $\mu$ indices indicate electrons, photons, tau leptons, jets and muons respectively. The $E_T^{\text{miss}}$ reconstruction thus requires as input reconstructed, calibrated physics objects and is based mainly on calorimeter data. Object selections will vary between analyses and so will the $E_T^{\text{miss}}$ accordingly. The “soft” term indicates measured energy not associated to any reconstructed hard object. It arises from underlying event activity and soft radiation from the hard objects. For run 2, the primary technique for estimating the soft term utilises track information. As tracks may be associated to a vertex, a track-based soft term is largely independent of the number of pile-up interactions in the event. This contrasts with a soft term estimated from calorimeter deposits. Such estimates has the advantage of being sensitive also to neutral particles (which do not leave a track in the inner detector), but the disadvantage of being sensitive to pile-up [20].
Chapter 5

Robustness Studies of the Pixel Clustering Neural Network Algorithm

In this chapter, the work carried out as ATLAS author qualification task will be presented. The work concerns the pixel clustering neural network (pixel NN) algorithm used to estimate the true particle position within clusters measured in the pixel detector. The main task of the pixel NNs is to improve track reconstruction (see Sec. 4.1) performance in so called dense environments, which are characterised by particles separated by distances comparable to the size of the detector readout elements. Such environments are common in the core of high-$p_T$ jets and in boosted topologies such as the decay of a boosted tau lepton. Many physics analyses depend on high performing track reconstruction in these environments, especially during the LHC run 2. For example, this concerns searches for heavy resonances, analyses depending on $b$-tagging (see Sec. 4.4) or energetic jets. In the ambiguity solving stage of the track reconstruction algorithm (see Sec. 4.1) tracks with shared clusters are penalised in their track score. This is a strong handle to reduce the amount of fake tracks. However, tracks with shared clusters are a natural consequence of dense environments. It is the job of the pixel NNs to recover such tracks which otherwise would be lost due to this penalty.

5.1 Pixel NN functionality

Currently there are three sets of NNs used in the pixel clustering algorithm. The first set is used to classify clusters as coming from one, two or more than two particles. This set is denoted the “particle multiplicity NN”. The second set estimates the pixel module local $x$ and and $y$ positions of the particles as they traversed the sensor surface. This set is denoted the “position NN”. The third set estimates
the uncertainties on the positions as estimated by the second set. When writing
this, studies are ongoing to revise the method with which to estimate the position
uncertainties. Therefore, this study is limited to the particle multiplicity NN and
the position NN. These two NNs share a common set of 60 input quantities, which
characterise the properties of a pixel cluster. They are

- a $7 \times 7$ pixel grid with the pixel charge (calibrated ToT) values in each pixel,
  where the central pixel is the geometrical centroid of the cluster,
- an array of size 7 with the longitudinal pixel pitches of the individual pixels
  to identify any column of pixels with longer pitches,
- a barrel- or end-cap boolean indicating the detector region the cluster is lo-
  cated in,
- an integer in the range $[0, 3]$ indicating the layer or disk of the pixel detector,
  where 0 corresponds to the IBL,$^1$
- the local incidence angles on the pixel module for the candidate track,$^2$ $\phi$ and
  $\theta$.

If a cluster is larger than seven pixels in either direction, it is flagged as being
created by multiple charged particles and is not fed to the particle multiplicity NN.
The NNs are called at certain stages during the track reconstruction, as explained
in the next section.

The particle multiplicity NN is trained on simulated events with the number of
particles traversing the pixel cluster as the target value. Each cluster is assigned a
class according to the number of particles it is associated with: one, two, or three
or more particles.

The position NN is a set of three separate NNs, one for each of the three particle
multiplicity classes introduced above. The output of the networks is a set of one,
two or three pairs of local $x$ and $y$ positions, depending on the particle multiplicity.
These NNs are trained with positions of the intersections of the particle trajectories
with the pixel module with respect to the cluster centroid as target values.

5.2 Pixel NN Utilisation Within the Track
Reconstruction Algorithm

The particle multiplicity NN is called in the ambiguity solver stage of the track
reconstruction, provided a pixel cluster is shared between tracks. If the particle

$^1$It was investigated whether training separate NNs for the pixel barrel and the IBL would
enhance the overall performance as compared to having this information given as an input. The
gain was found to be negligible.

$^2$For a cluster to which multiple particles have contributed, the local incidence angles of the
track with highest $p_T$ are used.
multiplicity NN flags the cluster as coming from more than one particle, the tracks sharing the cluster are not penalised.

The position NN is called at the end of the ambiguity solver stage when the final global track fit is performed. Depending on the output of the particle multiplicity NN it delivers one, two or three pairs of local $x$ and $y$ positions which are then used in the fit.

### 5.3 Pixel NN Validation Techniques

The NNs are validated using a statistically independent sample by comparing their response to the target values on which they have been trained. The classification of cluster particle multiplicity is determined by tuneable thresholds put on the particle multiplicity NN output. After the thresholds are fixed, a cluster is identified as single-particle or multi-particle depending on the output values of the particle multiplicity NN. In the following, the performance of the particle multiplicity NN will be evaluated using as a metric

- **single-particle fake rate**: fraction of single-particle clusters that are wrongly identified as multi-particle,

- **multi-particle efficiency**: fraction of multi-particle clusters that are correctly identified as such.

For the particle multiplicity NN studies, clusters with only one pixel are ignored as the performance of the particle multiplicity NN for these clusters is limited by the amount of information available.

The performance of the position NN is evaluated by examining the residual distributions calculated as the differences between the position NN estimates and the target values. In particular, the mean and the width of the distributions are studied, where the width is computed as the root mean square. The true number of particles contributing to a cluster will be used to determine which of the three position NNs will be used. The study of the performance of the position NN is limited to clusters that are two or more pixels wide in the corresponding local direction. Clusters that are only one pixel wide have a resolution in the corresponding direction which is predominantly determined by the pixel pitch. As such the position estimate for these clusters can not be improved by a NN clustering algorithm or any other technique, leaving these clusters insensitive to any variation. Clusters with a larger size are, apart from the pixel pitch, also influenced by the track incidence angles and the charge distribution. The number of pixels in the local $x$ direction will from hereon be denoted “rows”, while the number of pixels in the local $y$ direction will be denoted “columns”.
Chapter 5. Robustness Studies of the Pixel Clustering Neural Network Algorithm

5.4 Pixel NN Robustness Studies

This section outlines the robustness studies: the samples used, the different variations performed and the results.

5.4.1 Samples

This study uses simulated di-jet events, generated with Pythia 8.186 [21] at a centre of mass energy of $\sqrt{s} = 13$ TeV. Generator parameters corresponding to the A14 tune [22] are used together with the NNPDF2.3LO PDF set [23]. The sample is interfaced with a detailed GEANT4 [24] simulation of the ATLAS detector [25] and a pixel digitisation model.

To ensure a high fraction of multi-particle clusters, a filter is applied that requires at least one hadronic jet in the event with transverse momentum between 1.5 and 2 TeV at generator level. A high momentum jet has a number of highly collimated particles which are likely to create multi-particle clusters. Independent subsets of this sample are used to train the NNs under investigation and to study their robustness.

5.4.2 Remapping the Cluster Charge Distribution

The charge collection model in the pixel detector includes parameters like cross-talk between pixels and charge diffusion which affect the charge distribution within a cluster. To emulate such an effect, the charge within a pixel cluster is redistributed, while ensuring the total cluster charge and geometrical shape is preserved.

This variation is accomplished by letting each pixel in the cluster share a variable fraction of its charge with neighbouring pixels (where a neighbour is defined as a pixel having a common side and non-zero charge). This effectively smears the cluster's charge, resulting in the charge being more evenly distributed between the cluster's pixels. The cluster charge is considered more evenly distributed if the ratio between the charge of the pixel with most charge and the total cluster charge decreases. The procedure for performing the charge redistribution can be summarised as follows: for each pixel in the cluster with non-zero charge

1. generate a fractional charge amount to be shared with neighbouring pixels following a normal distribution with a width of 0, 3, 7, 12, 15 or 20% times the charge deposited in the pixel.

2. distribute this charge between the neighbouring pixels. This is done by randomly allocating fractions of the charge to the neighbouring pixels until the full amount has been distributed. The distribution is weighted by the pixel pitch of the sharing side (so that sharing charge across a longer side is more likely than across a shorter).

If the resulting smeared cluster has its charge more evenly distributed between its pixels, the cluster is updated to the smeared version.
5.4. *Pixel NN Robustness Studies*

In Fig. 5.1 the impact of remapping the cluster charge distribution on the single-particle fake rate and multi-particle efficiency are shown. The single-particle fake rate increases by approximately 5% for the pixel barrel when 20% of each pixel’s charge is shared between neighbouring pixels. The IBL is less sensitive to the variation. No dependence is observed for the multi-particle efficiency. The particle multiplicity NN is stable against charge variation at the cluster level, considering the large fraction to be shared to see a degradation in performance.

The single-particle position NN residual distribution widths as a function of charge smearing at the cluster level are shown in Fig. 5.2. The resolution degrades with increased smearing. The observed effect is more pronounced for the pixel barrel than for the IBL. The same behaviour is observed for the two- and three-particle position NNs, for both the local $x$ and the local $y$ direction.

For all particle multiplicities, the difference in the means between the residual distribution and the corresponding nominal distribution show no or a very small dependence ($< 1\mu m$) on this variation.

Considering that the largest variation magnitude ($\sigma_{\text{smear}} = 20\%$ of pixel charge) is a large smearing, the NNs may be deemed stable against this variation.

![Figure 5.1](image)

(a) Single-particle cluster, used by more than one track  
(b) Multi-particle cluster, used by more than one track

**Figure 5.1.** Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of the magnitude of smearing applied to the cluster (cluster level charge re-distribution). The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility.

5.4.3 *Cluster Charge Smearing at the Pixel Level*

This variation is probing the pixel charge resolution. It is performed by smearing each pixel’s charge with a normal distribution with width equal to 0 (default), 1,
Chapter 5. Robustness Studies of the Pixel Clustering Neural Network Algorithm

Figure 5.2. Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of the magnitude of smearing applied to the cluster (cluster level charge re-distribution). The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction.

2, 3, 4, 5 and 6 units of $\sigma_{\text{smear}}$, defined as

$$
\sigma_{\text{smear}} = \begin{cases} 
3\% \times [\text{pixel charge}], & \text{if } [\text{pixel charge}] > 6000 \text{ electrons} \\
250 \text{ electrons}, & \text{if } [\text{pixel charge}] < 6000 \text{ electrons}
\end{cases}
$$

The total charge in the cluster may be altered by this variation. The mean of the total cluster charge distribution is not altered, while the width of the distribution increases with increasing smearing. The magnitude of this variation is based on the residual difference between the calibrated charge (calculated from the pixels ToT) and the injected charge.

In Fig. 5.3 the impact of smearing the charge at the pixel level on the single-particle fake rate and multi-particle efficiency is shown. The single-particle fake rate increases by approximately 10% for the pixel barrel and the IBL for the largest variation corresponding to six standard deviations. At this level, the multi-particle efficiency decreases by a few percent for both the pixel barrel and the IBL. The IBL is slightly more sensitive than the pixel barrel. The particle multiplicity NN is more sensitive to this variation than to the the cluster level charge variation. This behaviour is expected as this variation will decrease the measured charge resolution.

The single particle residual distribution widths as a function of cluster charge smearing at the pixel level are shown in Fig. 5.4. The width grows with increasing smearing by roughly 9% and 12% for the local $x$ and local $y$ directions, respectively, for the largest variation magnitude. The same behaviour is observed for the two- and three-particle position NNs in both directions.
For both directions and for all particle multiplicities, the difference in the means between the residual distribution and the corresponding nominal distribution show no or a very small dependence (< 1\mu m) on this variation.

As a variation magnitude of six standard deviations is a very large smearing, the particle multiplicity NN and the position NNs can be considered stable against this type of variation.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5.3}
\caption{Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of smearing the cluster charge at the pixel level. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the x-axis for visibility.}
\end{figure}

\subsection{Charge Scaling}

This variation is meant to emulate the uncertainty on the charge calibration scale. Such an uncertainty affects a whole front-end circuit and is coherently propagated to all pixels in the cluster. The charge calibration scale is expected to be accurate to 10%. This variation is performed by multiplying each pixel’s charge by a factor equal to 0.7, 0.8, 0.9, 1 (default), 1.1, 1.2 and 1.3. Even if the varied pixel charge is below threshold, it is not removed from the cluster.

In Fig. 5.5 the single-particle fake rate and multi-particle efficiency are shown as a function of a constant pixel charge scale factor. Both the single-particle fake rate and the multi-particle efficiency increase with the scale factor. At 30% scaling up, the single-particle fake rate increases more than 100% for both the IBL and the pixel barrel. The multi-particle efficiency saturates once the charge in the cluster is scaled up by \sim 20%. The saturation occurs as the multi-particle efficiency approaches 100% efficiency. When scaling down the charge by 30%, the multi-particle efficiency decreases by more than 20% in both the IBL and the pixel barrel.
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Figure 5.4. Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of smearing of the cluster charge at the pixel level. The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction.

(a) Residual width local $x$

(b) Residual width local $y$

The single-particle fake rate also decreases by at least 30% for both the IBL and the pixel barrel. Effectively by increasing or decreasing the total cluster charge the cluster will look more or less like a multi-particle cluster.

The single-particle position NN residual distribution means and widths as a function of constant pixel charge scaling are shown in Fig. 5.6. The resolution decreases by a few percent for both scaling down and scaling up the charge. As expected the change in resolution is small as the relative weight of each pixel in the cluster remains constant under this variation. Greater degradations are observed in the resolution of two- and three-particle clusters, in particular in the local $x$ direction for both the mean and the width. A 10% degradation in resolution is seen when the charge is scaled by a factor $0.7$.

A small dependence on this variation is seen in the mean local $y$ residuals of the IBL. This implies that there are correlations used by the position NN that under this variation bias the result.

5.4.5 Charge Subtraction and Pixel Removal

This variation is probing the sensitivity to pixel ToT threshold variations. It is performed by subtracting charge values of $0$ (default), $100$, $250$, $500$, $750$ and $1000$ electrons from each pixel in the cluster. If the resulting charge is below the ToT threshold ($2500$ electrons for the IBL, $3500$ electrons for the remainder of the pixel barrel) the charge in that pixel is set to zero. The magnitude of the variations is
5.4. Pixel NN Robustness Studies

(a) Single-particle cluster, used by more than one track

(b) Multi-particle cluster, used by more than one track

Figure 5.5. Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of constant coherent scaling of the charge in each pixel in the cluster. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility.

based on the accuracy of the charge calibration scale, estimated to be 10%. In the simulated events, there are a small fraction of clusters where all pixels in the cluster fall below the threshold and subsequently not studied further.

The dimensions of the cluster are determined prior to the modification of the cluster, to ensure studying the same subset of clusters before and after the variation.

In Fig. 5.7 the results from subtracting fixed amounts of charge and subsequent removal of pixels from clusters are presented. The single-particle fake rate and multi-particle efficiency both decrease with increasing subtraction, with roughly 10% and 4% at 1000 electrons subtraction, respectively. This behaviour is expected as this variation will reduce the total cluster charge and possibly also its size, making the cluster more like a single-particle cluster both in terms of shape and overall charge. The kink observed when going from 400 electrons subtraction to 600 electrons subtraction for the IBL is due to clusters losing a pixel going below threshold, changing the cluster shape into single-pixel.

The single-particle position NN residual distribution widths as a function of the number of electrons removed from each pixel in the cluster is shown in Fig. 5.8.

The resolution degrades with increasing charge subtraction. For the local $x$ direction, the IBL is more sensitive to the variation than the pixel barrel and reaches roughly 30% degradation at 600 electrons subtraction. A degradation is expected, from altering the relative weighting between pixel charges in the cluster and from pixels going below threshold and therefore removing information used by the position NN otherwise. The same behaviour is observed for the two- and three-particle position NNs in both directions, but less pronounced (< 5% everywhere).
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Figure 5.6. Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of constant coherent scaling of the charge in each pixel in the cluster. The left plots show the difference between the mean of the residual distribution after scaling and the nominal mean, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The right figures show the corresponding ratio between the residual distribution width (computed as the root mean square) after scaling and the nominal width. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction.
For both directions and for all particle multiplicities, the difference in means between the residual distribution and the corresponding nominal distribution show no or very small dependence ($< 0.5\mu m$) under this variation.

![Graphs showing performance of the pixel neural network](image)

(a) Single-particle cluster, used by more than one track  
(b) Multi-particle cluster, used by more than one track

**Figure 5.7.** Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of a constant subtraction of charge from each pixel in the cluster, with subsequent removal of pixel if its modified charge goes below threshold. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The number of pixels in the cluster is calculated before the variation is performed. The points have been staggered along the $x$-axis for visibility.

### 5.4.6 Smearing the Incidence Angles

The track-to-module local incidence angles are smeared using a normal distribution with mean zero and width equal to 0 (default), 10, 25, 40 and 50 mrad\(^3\) for both $\theta$ and $\phi$. This variation probes the sensitivity to the track angular resolution and to detector misalignment effects.

In Fig. 5.9 the robustness of the particle multiplicity NN output against smearing the local incidence angles is shown. The same behaviour is observed for the pixel barrel and the IBL. At a smearing of 50 mrad, the single-particle fake rate increases by 5%, while the multi-particle efficiency decreases by 1%. This behaviour is expected as a smeared incidence angle leads to a different prediction of the expected charge deposit.

The single-particle position NN residual distribution widths as a function of local incidence angle smearing magnitude is shown in Fig. 5.10. The widths grow slightly with increasing angle smearing, and the pixel barrel is slightly more sensitive. A

---

\(^3\)The overall angular resolution is approximately 0.1 mrad.
smearing of the angle is expected to degrade the resolution, as a smeared angle might not match a certain cluster shape or total cluster charge.

For both directions and for all particle multiplicities, the difference in means between the residual distribution and the corresponding nominal distribution show no or very small dependence ($< 0.5\mu m$) on this variation.

Considering the smearing required to observe a degradation in performance is more than an order of magnitude larger than the track angular resolution, the particle multiplicity NN and the position NNs can be considered stable against this type of variation.

### 5.4.7 Summary of Robustness Studies

Tables 5.1 and 5.2 summarise the results of the robustness studies for the pixel barrel and for the IBL, respectively, for the largest variation magnitudes considered. For the cluster charge distribution remapping, the pixel charge smearing and the local incidence angle smearing, these magnitudes should be considered extreme. For the charge scaling and the constant charge subtraction these magnitudes are closer to expected uncertainties. In addition to the results discussed in the previous sections, the tables also list results for the position NNs used to assign positions to clusters with two and three or more particles. The difference in the means of the
5.4. **Pixel NN Robustness Studies**

### Table

<table>
<thead>
<tr>
<th>Smear (mrad)</th>
<th>Single-particle fake rate / Nominal</th>
<th>Multi-particle efficiency / Nominal</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.02%</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>±</td>
<td>0.03%</td>
<td>0.03%</td>
</tr>
<tr>
<td>Pixel barrel (Nominal = 9.67% 0.006 [mm])</td>
<td>IBL (Nominal = 8.78% 0.039 [mm])</td>
<td>IBL (Nominal = 9.3% 0.031 [mm])</td>
</tr>
</tbody>
</table>

### Figures

**Figure 5.9.** Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of smearing the local track-to-module incidence angles. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the x-axis for visibility.

**Figure 5.10.** Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of smearing the local track-to-module incidence angles. The y axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the x-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local x direction, while “columns” indicates the number of pixels in the local y direction.
residual distributions as compared to the nominal case show little (<3\mu m) or no dependence for all tested variations of the NN input variables.
Table 5.1. Summary of results of robustness studies, for clusters on the pixel barrel. All results for the particle multiplicity NN concern clusters with more than one pixel. All results for the position NNs concern clusters with more than one pixel in the direction of interest.

| Variation type | Constant coherent scaling of pixel charges | Cluster charge smearing, (cluster level) | Cluster charge smearing, (pixel level) | Constant charge subtraction with potential pixel removal | Local incidence angle smearing |
|----------------|------------------------------------------|----------------------------------------|----------------------------------------|------------------------------------------------ Trên cả hai NN với từ 1000 điện tử trừ tên | |
| Variation magnitude | Scale factor = 1.3 | Scale factor = 0.7 | $\sigma = 20\%$ of pixel charge | $\sigma = 6\sigma_{\text{smear}}$ | 1000 electrons subtraction | $\sigma_{\text{smear}} = 50\text{ mrad}$ |
| Performance change (%) of clusters with one generated particle | +113.6 ± 0.7 | −53.8 ± 0.4 | +6.27 ± 0.06 | +7.73 ± 0.07 | −12.44 ± 0.11 | +7.92 ± 0.07 |
| Correct identification rate of clusters generated by multiple particles | +2.05 ± 0.05 | −21.55 ± 0.17 | +0.201 ± 0.013 | −1.45 ± 0.04 | −2.00 ± 0.05 | −1.03 ± 0.03 |
| Resolution degradation (%) for clusters generated by | one particle, local $x$ direction | 2.43 ± 0.07 | 0.50 ± 0.07 | 17.98 ± 0.08 | 8.90 ± 0.08 | 16.23 ± 0.08 | 6.73 ± 0.07 |
| | one particle, local $y$ direction | 4.95 ± 0.09 | 2.54 ± 0.09 | 17.34 ± 0.10 | 12.61 ± 0.09 | 28.20 ± 0.11 | 1.81 ± 0.09 |
| | two particles, local $x$ direction | 1.8 ± 0.3 | 12.8 ± 0.3 | 4.4 ± 0.3 | 3.2 ± 0.3 | 2.8 ± 0.3 | 0.7 ± 0.3 |
| | | 2.3 ± 0.3 | 2.7 ± 0.3 | 1.4 ± 0.3 | 1.3 ± 0.3 | 2.2 ± 0.3 | 0.1 ± 0.3 |
| | | 1.7 ± 0.5 | 7.7 ± 0.5 | 3.0 ± 0.5 | 1.4 ± 0.5 | 1.1 ± 0.5 | 0.2 ± 0.4 |
| | | 0.9 ± 0.5 | 5.2 ± 0.5 | 1.2 ± 0.5 | 1.1 ± 0.5 | 1.2 ± 0.5 | 0.0 ± 0.4 |
### Table 5.2: Summary of results of robustness studies, for clusters on the IBL. All results for the particle multiplicity NN concern clusters with more than one pixel. All results for the position NN concern clusters with more than one pixel in the direction of interest.

<table>
<thead>
<tr>
<th>Variation type</th>
<th>Variation magnitude</th>
<th>misidentification rate of clusters with one generated particle (%)</th>
<th>correct identification rate of clusters generated by multiple particles (%)</th>
<th>Resolution degradation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant coherent scaling of pixel charges</td>
<td>Scale factor = 1.3</td>
<td>+144.6 ± 1.9</td>
<td>+2.99 ± 0.08</td>
<td>2.61 ± 0.15</td>
</tr>
<tr>
<td>Remapping the cluster charge distribution</td>
<td>Scale factor = 0.7</td>
<td>−33.2 ± 0.57</td>
<td>+0.163 ± 0.016</td>
<td>1.14 ± 0.03</td>
</tr>
<tr>
<td>Cluster charge smearing (pixel level)</td>
<td>σ smear = 20% of pixel charge</td>
<td>+2.52 ± 0.07</td>
<td>−7.21 ± 0.14</td>
<td>3.78 ± 0.15</td>
</tr>
<tr>
<td>Constant charge subtraction with potential pixel removal</td>
<td></td>
<td>+6.69 ± 0.13</td>
<td>0.5 ± 0.1</td>
<td>1.06 ± 0.04</td>
</tr>
<tr>
<td>Local incidence angle smearing</td>
<td>σ smear = 50 mrad</td>
<td>+12.0 ± 0.2</td>
<td>−4.67 ± 0.13</td>
<td>6.78 ± 0.13</td>
</tr>
</tbody>
</table>

*Note: The table entries represent changes in performance metrics for various robustness tests on the IBL. The results indicate the percentage change in the specified metrics for the particle multiplicity and position NNs, with respect to a baseline condition.
Chapter 6

Charged particle distributions in proton-proton interactions at $\sqrt{s} = 13$ TeV

Two complementary analyses measuring charged-particle distributions at $\sqrt{s} = 13$ TeV have been carried out by ATLAS so far. These were published separately but are very similar and to a large extent use the same method. The first is limited to the phase-space with tracks with $p_T > 500$ MeV [2], while the second extends to lower transverse-momentum using tracks with $p_T > 100$ MeV [26]. The author contributed to both analyses, but this chapter will summarise the latter one.

In the first section, the measurement and its motivation will be introduced. The analyses will then be described in the following sections, with a description of $pp$ collision simulation from a general perspective in Sec. 6.2.1. Section 6.8 outlines the authors own contribution to this study.

6.1 Introduction

In the 21 fb$^{-1}$ data set collected at $\sqrt{s} = 8$ TeV during run 1 of the LHC the average number of $pp$ interactions per bunch crossing was 21. For run 2 this number is expected to increase to around 40. Only a few of these interactions involve large momentum transfers while the rest are by most analyses considered to be background. These typically uninteresting interactions are commonly referred to as pile-up interactions. The measurement presented in this chapter aims at isolating pile-up interactions and find their charged particle distributions, and to compare them with the predictions of different models. A perturbative QCD treatment of
these low-momentum-transfer interactions is not possible due to the large value of the strong coupling constant at these energies. Instead, they are modelled with phenomenological models tuned to experimental data. This measurement thus provides valuable input to the art of modelling soft hadron collisions. From an experimental perspective, this measurement is important since pile-up interactions must be simulated as accurately as possible. Precise modelling is thus vital for almost all analyses carried out by ATLAS.

This study measures primary charged particle distributions by reconstructing charged particle tracks (see Sec. 4.1) using the ATLAS inner detector. The distributions are presented at particle level after unfolding detector inefficiencies. By primary is implied particles with a mean lifetime $\tau > 300$ ps, or decay products from particles with a mean lifetime $\tau < 30$ ps. Particles with a mean lifetime $30 < \tau < 300$ ps, mainly baryons with strange quark content, are considered secondary and excluded. The motivation for this is that these particles typically decay outside the innermost pixel layer and consequently the efficiency to reconstruct them is very low. This definition differs from previous analyses which also included these particles, e.g. in [27].

The events are required to have at least two primary tracks, and all tracks must have $p_T > 100$ MeV and lie within the inner detector acceptance; $|\eta| < 2.5$. The distributions measured are

$$\frac{1}{N_{ev}} \cdot \frac{dN_{ch}}{d\eta}, \quad \frac{1}{N_{ev}} \cdot \frac{1}{2\pi p_T} \cdot \frac{d^2N_{ch}}{d\eta dp_T}, \quad \frac{1}{N_{ev}} \cdot \frac{dN_{ev}}{dn_{ch}}$$

and

$$\langle p_T \rangle \text{ vs. } n_{ch}.$$ 

where $n_{ch}$ is the number of primary charged particles in an event, $N_{ev}$ is the number of events in the full data sample and $N_{ch}$ is the total number of primary charged particles.

### 6.2 Monte Carlo Generators and Tunes

This section describes the models used to simulate the events studied in this analysis. The modelling $pp$ collisions will first be summarised briefly from a general perspective in the coming section. Then, the specific Monte Carlo Event Generators used in this analysis will be described in Sec. 6.2.2.

#### 6.2.1 Simulating $pp$ collisions

Monte Carlo Event Generators are used to simulate the high-energy $pp$ collisions in the LHC. A sketch of a $pp$ collision is shown in Fig. 6.1, with the main ingredients to be simulated implied. These are [28],

- The hard interaction, i.e. the main high momentum transfer parton-parton subprocess. As such, this process is assumed to factorise from the rest of the event. Being in the perturbative regime, the outgoing particles’ properties may be computed through the relevant Feynman diagrams. Depending on
the generator’s scheme of modelling the hard interactions, parton density functions may or may not be used. If used, they determine which partons from the proton take part in the hard interaction.

- Parton showering, i.e. the evolution from the final state of the hard process to the point where perturbation theory breaks down and hadronisation begins \( (Q \sim 1 \text{ GeV}) \). It thus effectively adds higher-order corrections to the lowest-order calculation for the hard interaction mentioned in the previous bullet. This involves e.g. emission of gluons for the initial- and final state particles.

- Hadronisation, i.e. the mechanism responsible for taking coloured partons to colourless hadrons.

- Decays of unstable hadrons, i.e. the decays of short-lived hadrons into stable particles (possibly via other unstable hadrons).

- The underlying event, i.e. the activity not directly associated with the primary hard interaction. This includes multiple parton-parton interactions (MPIs; softer low-momentum transfer interactions between other partons not involved in the hard interaction) and beam remnants. This activity is mostly found in the forward regions.

Different programs exist on the market, which may simulate the full process or only some particular ingredient out of the ones listed above. The three different generators used in this analysis will be described in the next section.

### 6.2.2 Analysis-specific generators and tunes

The three different MC generators used for simulation in this study are \textsc{Pythia 8} \cite{21}, \textsc{EPOS} \cite{29} and \textsc{QgsJet-II} \cite{30}. They are used to measure different efficiencies, which are then input to the procedure of correcting the data distributions for detector effects. Furthermore, they are used to compare with the corrected particle-level distributions.

The first version of the widely used general-purpose generator \textit{Pythia} came out over 30 years ago. It aims at modelling all processes contributing to the full \( pp \) cross section and simultaneously models both the hard and soft part of the interaction. It has over 200 hard-coded subprocesses listed, mostly \( 2 \rightarrow 2 \) and \( 2 \rightarrow 1 \) processes. \textsc{Pythia 8} may be interfaced with other programs modelling specific processes. The cross section may be divided into an elastic and inelastic contribution, where the inelastic contribution may be further divided into a hard and a soft part. The soft part is made up of both diffractive and non-diffractive events (see Sec. 2.2). The diffractive events are modeled in \textsc{Pythia 8} through pomeron exchange. The pomeron is modeled as a colour singlet glueball state, but by QCD interactions also have a quark content. Single diffractive events involve radiation of one pomeron from one of the protons, colliding with the other proton. Through this scheme, the proton-pomeron collision may be treated as a normal hadron-hadron non-diffractive event. Double diffractive events are modelled through two pomeron emissions \cite{31}.
Figure 6.1. A sketch of a $pp$ collision and its different steps simulated by Monte Carlo event generators, from Ref. [28]. The grey ellipses represent the colliding protons. The red dot and its associated red straight lines indicate the hard parton-parton interaction and the outgoing partons respectively. The matrix element of this process may be computed from the relevant Feynman diagrams. Depending on the generator’s scheme of modelling the hard interactions, parton density functions may or may not be used. If used, they determine which partons from the proton take part in the hard interaction. The green and blue curly lines are initial state-and final state QCD radiation, referred to as parton showering. The white ellipses represent hadrons, extracted from a hadronisation model. These then decay into stable particles shown as yellow circles. The underlying event refers to the activity produced by beam remnants and interactions between partons not taking part in the primary interaction. This activity is not depicted in the figure, but the underlying-event-partons are represented by two black lines with arrows coming out from the grey ellipses. See text for further explanation.
Hadronisation is modelled in PYTHIA 8 with the phenomenological Lund string model. It models the gluonic field between two colour sources, such as a quark-antiquark system, as strings. The strings exert a constant force on the quarks, leading to a potential energy increasing linearly with their separation. At some separation cutoff scale the string breaks and colour-anticolour sources are produced and hadrons may be formed.

EPPOS is an event generator targeted at minimum bias hadronic interactions. It implements a parton based Gribov-Regge theory [32], which is an effective field theory describing hard and soft interactions simultaneously. The calculations do not rely on the standard parton distribution functions (PDFs) as is the case for e.g. PYTHIA 8. In EPPOS diffractive processes and their cross sections are calculated from first principles.

QGSJET-II is developed in the Reggeon Field Theory framework [33] and offers a phenomenological treatment of hadronic collisions at high energies. Like EPPOS, it models the diffractive scatterings directly.

In both PYTHIA 8 and EPPOS the effects of colour coherence is modeled. This refers to the tendency of outgoing partons to interfere with each other during their showering phase. It manifests itself in the presence of soft radiation between the coloured partons and a lack of such radiation elsewhere. This effect is important in dense parton environments and will effectively reduce the particle multiplicity in the final state due to multiple parton-parton interactions. QGSJET-II lacks a description of this effect.

The parameters of the phenomenological models may be set in any desired configuration, typically so as to reproduce a specific class of data such as minimum bias or underlying event. The full list of settings of a model is referred to as a tune. In Table 6.2.2 the MC generators and their respective tunes used in this analysis are listed.

<table>
<thead>
<tr>
<th>Generator</th>
<th>Version</th>
<th>Tune</th>
<th>Focus</th>
<th>PDF</th>
</tr>
</thead>
<tbody>
<tr>
<td>PYTHIA 8</td>
<td>8.185</td>
<td>A2</td>
<td>Minimum bias</td>
<td>MSTW2008LO</td>
</tr>
<tr>
<td>PYTHIA 8</td>
<td>8.186</td>
<td>MONASH</td>
<td>Minimum bias / Underlying event</td>
<td>NNPDF23LO</td>
</tr>
<tr>
<td>EPPOS</td>
<td>3.4</td>
<td>LHC</td>
<td>Minimum bias</td>
<td>-</td>
</tr>
<tr>
<td>QGSJET-II</td>
<td>II-04</td>
<td>default</td>
<td>Minimum bias</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 6.1. Summary of the MC generators and respective tunes used in the analysis for detector efficiency measurements and comparisons with particle-level distributions. The different tunes correspond to the specific settings of the model’s tunable parameters, which may be optimised for a certain physics process such as minimum bias events or the underlying event. The PYTHIA 8 A2 tune is provided by ATLAS while the other tunes are provided by the respective authors.

6.3 Event selection

During minimum bias data taking, the LHC is configured in a special setting with low beam currents and reduced beam focusing. The mean number of interactions
per bunch crossing is $\langle \mu \rangle = 0.005$. The minimum bias data is collected from proton-proton collisions in which the dedicated level-1 minimum bias trigger scintillators (MBTS) have recorded one or more counters above threshold on either side. These triggers have coverage $2.1 < |\eta| < 3.8$ and are mounted on two disks in front of the calorimeter end-caps, 3.6 m from the interaction point.

To reduce the number of background events and non-primary tracks, events are required to

- contain a primary vertex, reconstructed from at least two tracks with $p_T > 100$ MeV.
- not contain a second vertex with four or more associated tracks (to reduce the contribution from events with more than one interaction per bunch crossing).

The tracks in the events are required to

- have a transverse momentum $\geq 100$ MeV and $|\eta| < 2.5$,
- have at least 1 pixel hit,
- if a hit is expected in the innermost pixel layer (IBL), then one is required. If a track passes through an inactive IBL module, then a hit is required in the next layer if one is expected. This requirement suppresses tracks from secondary particles,
- have at least two, four or six SCT hits for tracks with $p_T < 300$ MeV, $p_T < 400$ MeV and $p_T > 400$ MeV respectively. If a track passes through an inactive layer, it is counted as a hit. This reduces the sensitivity to differences in the number of dead modules in data and simulation,
- the transverse impact parameter calculated with respect to the LHC beam line is required to fulfil $|d_0^{BL}| < 1.5$ mm.
- the longitudinal impact parameter is calculated with respect to the primary vertex. It is required that the distance between the primary vertex and the track at the point where we measure the $d_0^{BL}$ is $|\Delta(z_0 \sin \theta)| < 1.5$ mm,
- if $p_T > 10$ GeV, the track $\chi^2$ probability is required to be larger than 0.01. This suppresses the number of mis-measured tracks.

In total 9.3 million events are selected, containing 320 million selected tracks.

### 6.4 Background events and non-primary tracks

There are a number of sources which in rare cases generate similar event characteristics as single $pp$ collisions, entering this analysis as background. These are for example non-collision beam background and cosmic rays. Furthermore, in the recorded events, there are background contributions appearing as primary tracks. These are mainly secondary particles produced in hadronic interactions with the detector material.
6.4. Background events and non-primary tracks

6.4.1 Background events

There are three different sources of background events considered: non-collision beam background events, cosmic rays and events with more than one \( pp \) interaction in the same bunch crossing. The non-collision beam background is induced for example by proton-molecule interactions between the beam and residual gas in the beam pipe. It is estimated from events which pass the full event selection but observed when only one of the two beams are present. The rate of such events expected in the present data sample is estimated by measuring the timing difference between the MBTS triggers on one \((\eta > 0)\) and the other \((\eta < 0)\) side of the detector. The requirement of a primary vertex is particularly efficient in suppressing this background, and its contribution after applying all selections is found to be 0.009\% and therefore negligible and ignored.

Events from cosmic rays is estimated by comparing the expected rate to the event readout rate. This contribution is negligible as the former is expected to be 0.001 Hz and the latter 2 kHz.

An event with more than one \( pp \) interaction in the same bunch crossing has the potential to enter as background if the primary vertex can not be distinguished from an additional vertex. This contribution is mostly suppressed by the requirement of only one primary vertex in the event. The probability for vertex merging is estimated in a sample with at least two reconstructed vertices, from the distribution of the \( z \) distance between pairs of vertices; \( \Delta z \). This distribution has a deficit around \( \Delta z = 0 \) due to vertex merging, the size from which the fraction of events with a merged vertex can be estimated and is found to be 1.6\%. With the number of expected additional interactions being \( \langle \mu \rangle = 0.005 \), the contamination from events with merged pile up vertices is estimated to be smaller than 1.5 per mille everywhere and thus ignored.

6.4.2 Background to primary tracks

In the sample of collected events all non-primary tracks must be subtracted before correcting for detector effects. There are three dominant sources of such tracks: hadronic interactions, photon conversions and decays of long-lived particles. The two former are induced by interactions between hadrons and the ATLAS inner detector material. Such tracks are estimated using the fact that they are dominating the tails of the \( d_0^{BL} \) distribution. A sample is collected with the same track selection as listed in 6.3, but with the transverse impact parameter requirement removed. Templates for primary and non-primary particles are obtained from events simulated in PYTHIA 8 and used to fit the \( d_0^{BL} \) distribution of this data sample in the sideband regions. The fraction of non-primary tracks originating from electrons (typically created by photon conversions in the beam pipe) is inversely proportional to \( p_T \) and is approximately 50% in the region \( p_T < 500 \) MeV. Therefore, different templates are used for non-electrons and electrons in the region \( p_T < 500 \) MeV. The fits are performed in the region \( 4 < |d_0^{BL}| < 9 \) mm in steps of 50 MeV in nine \( p_T \) intervals. The fit for the region \( 100 \) MeV \(< p_T < 150 \) MeV is shown in Fig. 6.2.
together with the data and the simulation. After normalising the simulation predictions to data in the fit region, the templates are used to predict the number of non-primary tracks in the $|d_0^{BL}| < 1.5$ mm region.

The number of tracks originating from strange baryons is estimated with EPOS. On average, they constitute less than 0.01% of all tracks, whereas for $p_T > 20$ GeV the fraction is estimated to 0.03 ± 0.01.

There is also a small contribution to the number of non-primary tracks originating from fake tracks, i.e. tracks reconstructed from random combinations of measurements. It is studied in simulation after the full event and track selection have been applied, and estimated as the number of tracks which can not be matched to a generated particle. This background is small due to the low track multiplicity in minimum bias events; the resulting fraction of tracks identified as fake is found to be below 1% for all $p_T$ and $\eta$ bins.

6.5 Selection efficiencies

To obtain inclusive spectra of charged particles the measurements must be corrected for detector inefficiencies. This section lists the different inefficiencies which are then input to the correction procedure described in Section 6.6.

6.5.1 Trigger efficiency

The efficiency of the MBTS triggers is measured in data sample collected with randomly-seeded control trigger. The control trigger selects events randomly at L1 and are then filtered through the HLT by requiring at least one reconstructed track with $p_T > 200$ MeV. The efficiency is defined as the ratio between the number of events in which the MBTS trigger fired, and the total number of events in the control sample. The resulting efficiency is shown in Fig. 6.3(a) as a function of $n_{\text{no-\,z}}^{\text{sel}}$; the number of selected tracks in events satisfying the requirements as listed in Sec. 6.3 but with the longitudinal impact parameter removed. The efficiency increases from 96.5±0.4% for $n_{\text{sel}}^{\text{no-\,z}} = 2$ towards 1 for larger $n_{\text{sel}}^{\text{no-\,z}}$. Dropping the longitudinal impact parameter requirement is motivated by the possible presence of correlation between trigger efficiency and vertex efficiency (the latter explained in the coming section).

6.5.2 Vertex efficiency

The vertex efficiency is defined as the ratio between the number of events with a reconstructed vertex, to the total number of triggered events. It is given as a function of $n_{\text{sel}}^{\text{no-\,z}}$ and measured to 87% for $n_{\text{sel}}^{\text{no-\,z}} = 2$ to rapidly approach 100% for higher $n_{\text{sel}}^{\text{no-\,z}}$, as shown in Fig. 6.3(b). For events with $n_{\text{sel}}^{\text{no-\,z}} = 2$ the efficiency is also parametrised in $\Delta z_{\text{tracks}}$, the difference between the longitudinal impact parameter between the two tracks. The vertex efficiency for these events falls off linearly from approximately 91% for $\Delta z_{\text{tracks}} < 1$ mm to go below 40% for $\Delta z_{\text{tracks}} > 9$ mm.
6.5. Selection efficiencies

![Figure 6.2](image)

**Figure 6.2.** The $d_{0}^{\text{BL}}$ distribution for data and PYTHIA 8 simulation for tracks with $100 < p_{T} < 150$ MeV, with the ratio between data and simulation in the lower panel. Tracks from different non-primary sources are indicated in the coloured dashed and dotted lines, and are normalised to the data in the region $4 < |d_{0}^{\text{BL}}| < 9$ mm. The normalised predictions are then summed and used as estimate for the number of non-primary tracks in the region $|d_{0}^{\text{BL}}| < 1.5$ mm indicated by the dashed vertical lines. The error bars on the data points are statistical uncertainties. Figure from Ref. [26].
6.5.3 Track reconstruction efficiency

The primary track reconstruction efficiency, $\epsilon_{\text{trk}}$, is estimated using simulation. It is parametrised in two dimensions as a function of $p_T$ and $\eta$ of the generated particles, and defined as

$$\epsilon_{\text{trk}}(p_T, \eta) = \frac{N_{\text{rec}}^\text{matched}(p_T, \eta)}{N_{\text{gen}}(p_T, \eta)}$$

where $N_{\text{rec}}^\text{matched}$ are the number of reconstructed tracks matched to a generated particle and $N_{\text{gen}}$ is the number of generated particles. A reconstructed track is defined as matched to a generated particle if a weighted fraction of the track’s inner detector measurements originating from the generated particle exceeds 50%. The measurements are weighted such that the three different inner detector subsystems are given equal weight. The primary track reconstruction efficiency is shown as a function of $p_T$ and $\eta$ in Fig. 6.3(c) and Fig. 6.3(d) respectively. For the region $100 < p_T < 125$ MeV the track reconstruction is 27.5%, it then increases from approximately 62% to 76% between $p_T = 125$ MeV and $p_T = 200$ MeV to finally increases slowly to approximately 87% for the highest-$p_T$ bin. The efficiency is in general higher for the central region, approximately 80%, where particles have relatively less material to traverse as compared to the forward regions. The uncertainties on the track reconstruction efficiency originates mainly from imprecise knowledge of the detector material.

6.6 Correction procedure and unfolding method

The recovering of inclusive charged particle spectra from the observed track distributions involves two steps; the application of event- and track-by-track based weights constructed from the inefficiencies presented in the previous section, and a Bayesian unfolding to correct for bin-by-bin migration in the distribution, arising from limited resolution. The event based weight corrects for trigger and vertex efficiencies according to

$$w_{\text{ev}}(n_{\text{sel}}^{\text{no-z}}, \Delta z_{\text{tracks}}) = \frac{1}{\epsilon_{\text{trig}}(n_{\text{sel}}^{\text{no-z}})} \cdot \frac{1}{\epsilon_{\text{vtx}}(n_{\text{sel}}^{\text{no-z}}, \Delta z_{\text{tracks}})}.$$  (6.1)

After the event weight has been applied, the $p_T$ and $\eta$ distributions of tracks are weighted by the following weight expression

$$w_{\text{trk}}(p_T, \eta) = \frac{1}{\epsilon_{\text{trk}}(p_T, \eta)} \cdot [1 - f_{\text{fake}}(p_T, \eta) - f_{\text{sb}}(p_T, \eta) - f_{\text{sec}}(p_T, \eta) - f_{\text{okr}}(p_T, \eta)].$$  (6.2)

where $f_{\text{fake}}(p_T, \eta)$ correspond to the fraction of fake tracks, $f_{\text{sb}}(p_T, \eta)$ to the fraction of strange baryons, $f_{\text{sec}}(p_T, \eta)$ to the fraction of secondary particles and $f_{\text{okr}}(p_T, \eta)$ to the fraction of particles originating from particles outside of the kinematical
Figure 6.3. Different selection efficiencies in this analysis. The top figures show efficiencies related to the event selection; the trigger (left) and vertex (right) efficiency as a function of the number of reconstructed tracks. The trigger efficiency is measured using a control trigger; the vertex efficiency is measured as the fraction of events which contain a primary vertex out of the total number of triggered events. The bottom figures show the primary track reconstruction efficiency as a function of $p_T$ (left) and $\eta$ (right), estimated in simulation. These efficiencies are put into a weight expression which is applied to the data to unfold it to particle level. The error bars are statistical uncertainties, the green shaded areas are the statistical and systematic uncertainties added in quadrature. Figures from Ref. [26].
acceptance. \( f_{\text{okr}}(p_T, \eta) \) and a corresponding systematic uncertainty was estimated by the author, see Sec. 6.8.

The iterative Bayesian unfolding method used is explained in Ref. [34]. A brief description will be given here. Consider a set of causes and a corresponding set of possible effects or responses. These may be pictured as the different bins in a binned distribution. A given cause may produce different responses, but a given response (i.e. a measurement) does not map to a unique cause. This is due to resolution effects causing bin-to-bin migration and due to loss of response caused by inefficiency. Inversion of the migration matrix is not possible, but Bayes’ theorem provides a way of estimating the probability for a certain cause, given a certain response. This is realised using as input knowledge about the migration and inefficiency. In practice, to unfold a distribution, one first needs to fill the migration matrix and compute efficiencies. These are then used together with the full response to compute the posterior probability for each cause. As the prior probability for a cause enters this calculation, this process may be repeated with the updated best guesses obtained in the first iteration used as priors in the next. The iteration procedure then terminated once some predetermined convergence criteria is met and the unfolding is then finalised.

6.7 Results and interpretation

In Fig. 6.4 and Fig. 6.5 the resulting unfolded particle multiplicity distributions are shown.

The different MC models all show the same shape in the pseudorapidity distribution shown in Fig. 6.4(a). QGSJET-II, EPOS and PYTHIA 8 MONASH describe the data distribution well, while PYTHIA 8 A2 under-predicts the data in terms of normalisation.

The particle multiplicity as a function of \( p_T \) is shown in Fig. 6.4(b). EPOS predicts the data the best in general. For \( p_T < 200 \) MeV all models under-predict the data. QGSJET-II and PYTHIA 8 MONASH mostly overestimate the data for \( p_T > 400 \) MeV, of the order 10% at \( p_T = 500 \) MeV. PYTHIA 8 A2 underestimates the data for \( p_T > 800 \) MeV.

The particle multiplicity distribution is shown in Fig. 6.5(a). PYTHIA 8 A2 describe the intermediate region \( 30 < n_{\text{ch}} < 70 \) very well, but underestimates the higher \( n_{\text{ch}} \) region and the lowest \( n_{\text{ch}} \) region. The other three models mostly under-predict the data in the intermediate region, up to 20%. EPOS best describes the low-\( n_{\text{ch}} \) region and the high-\( n_{\text{ch}} \) region. QGSJET-II overestimates the data at high \( n_{\text{ch}} \) values and underestimates the data in the intermediate region. The general shape is fairly well reproduced by all models and the largest discrepancies are found for the very highest \( n_{\text{ch}} \) region.

In Fig. 6.5(b) the average transverse momentum is shown as a function of \( n_{\text{ch}} \). EPOS predicts the data best, with almost perfect agreement for \( n_{\text{ch}} > 50 \). It underestimates the lower \( n_{\text{ch}} \) region with up to 10%. PYTHIA 8 A2 and PYTHIA 8 MONASH have both similar shapes as EPOS and the data, but over-predicts the
region $n_{ch} > 20$ with up to 10\%. PYTHIA 8 MONASH show good agreement for the very lowest $n_{ch}$ region. The QGSJET-II model, lacking a colour coherence description, predicts mostly a flat shape and does not predict the data well.

$$\eta$$ distribution shape is the same for all models and reproduce the data well, but PYTHIA 8 A2 underestimates the data in terms of normalisation. The $p_T$ distribution is reproduced best by EPOS, especially for $p_T > 200$ MeV, while all models underestimates the data at lower $p_T$ values. The error bars denote statistical uncertainties, the shaded areas show the statistical uncertainties and the systematics uncertainties added in quadrature.

### Figure 6.4.

Primary charged-particle distributions as a function of pseudorapidity (a) and transverse momentum (b). The data is shown in black points, the coloured curves are different MC models. The $\eta$ distribution shape is the same for all models and reproduce the data well, but PYTHIA 8 A2 underestimates the data in terms of normalisation. The $p_T$ distribution is reproduced best by EPOS, especially for $p_T > 200$ MeV, while all models underestimates the data at lower $p_T$ values. The error bars denote statistical uncertainties, the shaded areas show the statistical uncertainties and the systematics uncertainties added in quadrature.

#### 6.8 Migration of particles inside and outside the fiducial phase space

The fraction of reconstructed selected tracks which originate from particles outside the kinematic range, $f_{okr}(p_T, \eta)$, is estimated from simulation; more specifically the PYTHIA 8 A2 model. The systematic uncertainty on this fraction is estimated as differences in the fraction between (a) samples from different MC models, to probe the uncertainty on shape of the distribution near the acceptance boundary, and (b) samples with and without material distortions, to probe imperfections in
Figure 6.5. (a) The distribution of the number of charged particles in an event. (b) The average transverse momentum as a function of the number of charged particles in an event. The $n_{\text{ch}}$ distribution is predicted fairly well by all generators in terms of shape. EPOS show the best agreement in the very lowest $n_{\text{ch}}$ region and the very highest $n_{\text{ch}}$ region, while PYTHIA 8 A2 show best agreement in the intermediate region. The $\langle p_T \rangle$ vs. $n_{\text{ch}}$ distribution is described well by both PYTHIA 8 models and EPOS, the latter predicting the high $n_{\text{ch}}$ region exceptionally well. QGSJET-II does not predict the data well. The error bars denote statistical uncertainties, the shaded areas are statistical uncertainties and systematic uncertainties added in quadrature. Figures from [26].
6.8. Migration of particles inside and outside the fiducial phase space

- **PYTHIA 8 A2 mixed** (the relative cross section weighted sum of the three above samples) (“A2_Mixed”),
- **PYTHIA 8 MONASH nondiffractive** ("Monash_ND")
- **PYTHIA 8 MONASH singlediffractive** ("Monash_SD")
- **PYTHIA 8 MONASH doublediffractive** ("Monash_DD")
- **PYTHIA 8 MONASH mixed** (the relative cross section weighted sum of the three above samples) ("Monash_Mixed")
- **EPOS** ("EPOS")
- **HERWIG++** ("Herwig")
- **PYTHIA 8 A2 nondiffractive with 2.5%, 5% and 10% extra Inner Detector material**, ("A2_ND_em2p5", "A2_ND_em5", "A2_ND_em10"). This inclusion of this sample is motivated by the uncertainty on the overall amount of material in the inner detector.
- **PYTHIA 8 A2 nondiffractive with 10% extra IBL detector material** ("A2_ND_emIBL10"). The inclusion of this sample is motivated by the uncertainty on the IBL material specifically. The IBL was inserted for run 2 and it was discovered that the simulation was lacking certain parts of its passive material.
- **PYTHIA 8 A2 nondiffractive with 2×10% extra ID material in the forward η regions only, where for |η| > 2.2 the number of migrated tracks is generated with 10% extra material and scaled up by factor two ("A2_ND_emHighEta").** The inclusion of this sample is motivated by the observation that a specific piece of material in the high-η region was not well simulated.

The η migration is summarised in the plots in Fig. 6.6. The left figure is showing the fraction of selected tracks originating from primary particles with |η| > 2.5. The bulk (∼ 75%) of primary particles that migrate are found within 2.5 < |η| < 2.50625. The right plot is showing the migration to the region 2.4 < |η| < 2.5 for the different samples. The major difference in migration is found in the high-η distorted material sample, causing a degradation of resolution.

The pT migration is summarised in the plots in Fig. 6.7. The left plot is showing the number of primary tracks originating from particles from pT < 100 MeV, after subtracting the number of particles migrating out of acceptance (from pT > 100 MeV to pT < 100 MeV), normalised to the number of selected tracks. The right figure is showing the difference in residual pT migration in the region 100 < pT < 125 MeV. As for the η migration, the biggest changes in the number of migrated tracks are caused by material distortions.

The difference in the total migration between the samples is considered a systematic uncertainty. It is calculated as the absolute value of the difference in
Figure 6.6. Primary particles migrating from $|\eta| > 2.5$ to be reconstructed as tracks with $|\eta| < 2.5$. Left: Fraction of selected tracks originating from particles with $|\eta| > 2.5$. Right: Sample comparison for $\eta$ migration.

Figure 6.7. Primary particles migrating from $p_T < 0.1$ GeV to be reconstructed as tracks with $p_T > 0.1$ GeV. Left: Fraction of selected tracks originating from $p_T$ migrated particles for the Pythia8 A2 mixed sample. Right: Sample comparison for $p_T$ migration.
6.8. Migration of particles inside and outside the fiducial phase space

Migration fractions in the 2D $|\eta|$ versus $p_T$ distribution. The four different contributions, which are added up in quadrature, and their relative sizes are listed in Table 6.2. The major contributor to both $p_T$ and $\eta$ migration uncertainty is the high-$\eta$ material sample.

Table 6.2. Summary table of the systematic uncertainties on the corrections applied to tracks originating from outside of the kinematical region ($p_T$ and $\eta$ acceptance). The largest contributions are from the material uncertainties (extra IBL and extra high $\eta$ material) and the generator differences. “ND” stands for nondiffractive.

<table>
<thead>
<tr>
<th>Systematic uncertainty</th>
<th>Calculated as difference between samples</th>
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<th>Fraction of total uncertainty ($\eta$)</th>
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<tr>
<td>Generator</td>
<td>herwig++ and pythia 8 Monash</td>
<td>19%</td>
<td>12%</td>
</tr>
<tr>
<td>Inner Detector extra material</td>
<td>5% extra ID material and pythia 8 ND</td>
<td>1%</td>
<td>4%</td>
</tr>
<tr>
<td>IBL corrected material</td>
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<td>4%</td>
<td>4%</td>
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<tr>
<td>High $\eta$ extra material</td>
<td>2×10% extra ID material ($</td>
<td>\eta</td>
<td>&gt; 2.2$) and pythia 8 ND</td>
</tr>
</tbody>
</table>

The total size of the out of phase space (OOPS) correction in various $\eta$ and $p_T$ bins is shown in Fig. 6.8 on the left hand side. On the right hand side, the resulting relative systematic uncertainty histogram is shown. The correction is largest for the lowest $p_T$ and highest $\eta$ bin, but the relative uncertainty is still smaller than 4.5%.

6.8.1 The $p_T > 500$ MeV analysis

For the analysis with tracks with $p_T > 500$ MeV, the migration of tracks was also estimated. Due to the better transverse momentum resolution at this higher transverse momentum the migration uncertainties are negligible as compared to other contributions to the track reconstruction efficiency uncertainty.
Chapter 6. Charged particle distributions in proton-proton interactions at $\sqrt{s} = 13$ TeV

Figure 6.8. (a) Estimated fraction of tracks originating from particles outside the kinematic acceptance (b) The total systematic uncertainty on this fraction, estimated from simulation as the quadratic sum of different contributions. The fraction of tracks estimated to come from outside the kinematic acceptance are input to the track reconstruction efficiency weight; effectively they are subtracted from the measured value in data. The systematic uncertainty on the fraction results in a systematic uncertainty on the track reconstruction efficiency.
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5.1 Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of the magnitude of smearing applied to the cluster (cluster level charge re-distribution). The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility. 35

5.2 Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of the magnitude of smearing applied to the cluster (cluster level charge re-distribution). The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction. 36

5.3 Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of smearing the cluster charge at the pixel level. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility. 37

5.4 Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of smearing of the cluster charge at the pixel level. The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction. 38
5.5 Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of constant coherent scaling of the charge in each pixel in the cluster. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility.

5.6 Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of constant coherent scaling of the charge in each pixel in the cluster. The left plots show the difference between the mean of the residual distribution after scaling and the nominal mean, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The right figures show the corresponding ratio between the residual distribution width (computed as the root mean square) after scaling and the nominal width. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction.

5.7 Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of a constant subtraction of charge from each pixel in the cluster, with subsequent removal of pixel if its modified charge goes below threshold. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The number of pixels in the cluster is calculated before the variation is performed. The points have been staggered along the $x$-axis for visibility.

5.8 Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of a constant subtraction of charge from each pixel in the cluster, with subsequent removal of pixel if its modified charge goes below threshold. The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after the variation and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction. The number of rows and columns are calculated before the variation is performed.
5.9 Performance of the pixel neural network used to identify clusters created by multiple charged particles, as a function of smearing the local track-to-module incidence angles. The left figure shows the rate at which the neural network wrongly identifies clusters with one generated particle as clusters with multiple particles. The right figure shows the rate at which the neural network correctly identifies clusters generated by multiple particles as such. The points have been staggered along the $x$-axis for visibility. 

5.10 Performance of the pixel neural networks used to estimate positions of particles in a pixel cluster, as a function of smearing the local track-to-module incidence angles. The $y$ axes show the ratio between the width (computed as the root mean square) of the residual distribution after smearing and the nominal width, where the residual is calculated as the difference between the neural network’s estimate and the intersection with the module of the simulated particle. The points have been staggered along the $x$-axis for visibility. “Rows” indicates the number of pixels in the cluster in the local $x$ direction, while “columns” indicates the number of pixels in the local $y$ direction.

6.1 A sketch of a $pp$ collision and its different steps simulated by Monte Carlo event generators, from Ref. [28]. The grey ellipses represent the colliding protons. The red dot and its associated red straight lines indicate the hard parton-parton interaction and the outgoing partons respectively. The matrix element of this process may be computed from the relevant Feynman diagrams. Depending on the generator’s scheme of modelling the hard interactions, parton density functions may or may not be used. If used, they determine which partons from the proton take part in the hard interaction. The green and blue curly lines are initial state- and final state QCD radiation, referred to as parton showering. The white ellipses represent hadrons, extracted from a hadronisation model. These then decay into stable particles shown as yellow circles. The underlying event refers to the activity produced by beam remnants and interactions between partons not taking part in the primary interaction. This activity is not depicted in the figure, but the underlying-event-partons are represented by two black lines with arrows coming out from the grey ellipses. See text for further explanation.
6.2 The $d_{0}^{BL}$ distribution for data and PYTHIA 8 simulation for tracks with $100 < p_{T} < 150$ MeV, with the ratio between data and simulation in the lower panel. Tracks from different non-primary sources are indicated in the coloured dashed and dotted lines, and are normalised to the data in the region $4 < |d_{0}^{BL}| < 9$ mm. The normalised predictions are then summed and used as estimate for the number of non-primary tracks in the region $|d_{0}^{BL}| < 1.5$ mm indicated by the dashed vertical lines. The error bars on the data points are statistical uncertainties. Figure from Ref. [26].

6.3 Different selection efficiencies in this analysis. The top figures show efficiencies related to the event selection; the trigger (left) and vertex (right) efficiency as a function of the number of reconstructed tracks. The trigger efficiency is measured using a control trigger; the vertex efficiency is measured as the fraction of events which contain a primary vertex out of the total number of triggered events. The bottom figures show the primary track reconstruction efficiency as a function of $p_{T}$ (left) and $\eta$ (right), estimated in simulation. These efficiencies are put into a weight expression which is applied to the data to unfold it to particle level. The error bars are statistical uncertainties, the green shaded areas are the statistical and systematic uncertainties added in quadrature. Figures from Ref. [26].

6.4 Primary charged-particle distributions as a function of pseudorapidity (a) and transverse momentum (b). The data is shown in black points, the coloured curves are different MC models. The $\eta$ distribution shape is the same for all models and reproduce the data well, but PYTHIA 8 A2 underestimates the data in terms of normalisation. The $p_{T}$ distribution is reproduced best by EPOS, especially for $p_{T} > 200$ MeV, while all models underestimates the data at lower $p_{T}$ values. The error bars denote statistical uncertainties, the shaded areas show the statistical uncertainties and the systematics uncertainties added in quadrature.

6.5 (a) The distribution of the number of charged particles in an event (b) The average transverse momentum as a function of the number of charged particles in an event. The $n_{ch}$ distribution is predicted fairly well by all generators in terms of shape. EPOS show the best agreement in the very lowest $n_{ch}$ region and the very highest $n_{ch}$ region, while PYTHIA 8 A2 show best agreement in the intermediate region. The $\langle p_{T} \rangle$ vs. $n_{ch}$ distribution is described well by both PYTHIA 8 models and EPOS, the latter predicting the high $n_{ch}$ region exceptionally well. QGSJET-II does not predict the data well. The error bars denote statistical uncertainties, the shaded areas are statistical uncertainties and systematic uncertainties added in quadrature. Figures from [26].
6.6 Primary particles migrating from $|\eta| > 2.5$ to be reconstructed as tracks with $|\eta| < 2.5$. Left: Fraction of selected tracks originating from particles with $|\eta| > 2.5$. Right: Sample comparison for $\eta$ migration. ........................................... 62

6.7 Primary particles migrating from $p_T < 0.1$ GeV to be reconstructed as tracks with $p_T > 0.1$ GeV. Left: Fraction of selected tracks originating from $p_T$ migrated particles for the Pythia8 A2 mixed sample. Right: Sample comparison for $p_T$ migration. ........................................... 62

6.8 (a) Estimated fraction of tracks originating from particles outside the kinematic acceptance (b) The total systematic uncertainty on this fraction, estimated from simulation as the quadratic sum of different contributions. The fraction of tracks estimated to come from outside the kinematic acceptance are input to the track reconstruction efficiency weight; effectively they are subtracted from the measured value in data. The systematic uncertainty on the fraction results in a systematic uncertainty on the track reconstruction efficiency. . . 64
Bibliography


