Anomaly Detection in $Y \rightarrow XH$ & FEB2 Upgrades of the ATLAS Detector

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Abstract

The aim of this report is to discuss two disjoint topics: (1) The implementation of anomaly detection techniques to a boosted ATLAS analysis of a generic TeV-scale particle $Y$ decaying to a new particle $X$ and a Standard Model Higgs boson. This is done by introducing a variational recurrent neural network (VRNN)-based anomaly score that allows for sensitivity to anomalous energy deposition in the otherwise homogeneous QCD background. The performance of the anomaly score is evaluated across samples corresponding to various signal hypotheses, and a selection on anomaly score is shown to yield between 5-30% increase in significance of signal over background. (2) The development of new front-end boards (FEB2) to replace the current front-end readout system in the ATLAS detector, in order to accommodate for the requirements of the high luminosity LHC. Currently available is a slice of the final FEB2 boards, the slice testboard. The focus of this portion of the report is on software development, in particular establishing a procedure that allows the various clock parameters of the chips on the board to be determined.
Contents

1 Introduction ........................................................................................................... 3
   1.1 The Standard Model ......................................................................................... 3
   1.2 Instrumentation ............................................................................................... 4
      1.2.1 The Large Hadron Collider .................................................................... 4
      1.2.2 The ATLAS Detector ......................................................................... 5

2 Anomaly Detection in $Y \to XH$ ........................................................................... 7
   2.1 $Y \to XH$ ........................................................................................................ 7
      2.1.1 Overview ................................................................................................. 7
      2.1.2 Boosted Jet Topologies ......................................................................... 9
      2.1.3 Jet Tagging .......................................................................................... 10
   2.2 Anomaly Detection ......................................................................................... 10
   2.3 Performance of Anomaly Score in $Y \to XH$ .................................................. 11
      2.3.1 Training Performance ........................................................................... 12
      2.3.2 Analysis Performance ......................................................................... 15
      2.3.3 Conclusions ......................................................................................... 19

3 FEB2 Upgrades of the ATLAS Detector ............................................................... 20
   3.1 The HL-LHC .................................................................................................. 20
   3.2 Slice Testboard .............................................................................................. 22
      3.2.1 Clock Scan ............................................................................................ 24
      3.2.2 Conclusions ......................................................................................... 27

4 Acknowledgements ............................................................................................... 27

5 References ............................................................................................................ 28
1 Introduction

1.1 The Standard Model

The Standard Model (SM) of particle physics is currently our best theory for describing particles and their interactions. It is a culmination of many years of work between experimentalists and theorists alike, with its present formulation having been finalized in the 1970s. [1] The current SM of particle physics is shown in figure 1.

![Figure 1: The Standard Model of particle physics: quarks and leptons form the fermionic sector, shown in purple and green; while the force mediators and the Higgs form the bosonic sector, shown in orange and yellow.](image)

Particles in the standard model are divided into two groups: fermions and bosons. Fermionic matter encompasses both the quark and lepton sector of the SM, and any composite particle that has a half-integer spin. These sectors are further divided into three mass generations, grouping lighter to heavier particles together. The lightest charged particles of each sector are stable and do not decay, while the subsequent generations have short lifetimes and are only ever observed in higher energy regimes. Neutrinos from every sector however do not decay, and further barely interact with other types of matter.

Bosonic matter encompasses the force-mediators of the SM, as well as any fundamental or composite particle with integer spin. In the SM the force-mediating bosons are further
classified as gauge bosons, quanta of the gauge fields in the theory all carrying spin 1. These include the photon, the mediator of the electromagnetic (EM) force; the gluon, the mediator of the strong force; and the $W^\pm$ and $Z^0$ bosons, the mediators of the weak force. The Higgs boson is in contrast a scalar boson with spin 0, and a manifestation of excitations of the Higgs field. The existence of the Higgs field and its interaction with the elementary particles in the SM is subsequently what gives rise to their masses through the Higgs mechanism.

Decades of experiments have added a robust credibility to the SM, with early predictions such as the existence of quarks, the $W^\pm$ and $Z^0$ bosons, and the Higgs boson all being confirmed by experiment in the past 40 years. Despite this robustness, the SM is inherently incomplete, with no account for gravity or dark matter. The SM also fails to explain the matter-antimatter asymmetry, dark energy, and the theory contains 19 free parameters – such as the masses of the fundamental particles – that have to be tuned by experiment and are not explained. The incompleteness of the SM has motivated many additional “Beyond the Standard Model” (BSM) theories to patch these inconsistencies, and consequently detector searches for evidence of BSM physics.

1.2 Instrumentation

1.2.1 The Large Hadron Collider

To achieve the necessary energy scales to study BSM physics, the Large Hadron Collider (LHC) was built under the European Council for Nuclear Research (CERN) in Geneva, Switzerland. The LHC is a proton-proton collider which lies in an underground 27 km tunnel, straddling the French-Swiss border. It is the culmination of past collider experiments at CERN which now are integral components to the LHC’s accelerating process; a schematic in figure 2 shows the accelerator complex at CERN and the injector rings to the LHC.

The first step in the LHC accelerator chain is to strip Hydrogen atoms of their electrons to yield protons. These protons are then fed to a linear accelerator (LINAC) which accelerates them to 50 MeV, then to the Proton Synchrotron Booster (PSB) accelerating them to 1.4 GeV, to the Proton Synchrotron (PS) towards 25 GeV, and to the Super Proton Synchrotron (SPS) towards 450 GeV. The beam from the SPS is then fed into the LHC, where the proton beam is accelerated to upwards of 7 TeV. These yield collisions with a center of mass energy of $\sqrt{s} = 14$ TeV. [2] The acceleration process itself is done by radio frequency (RF) cavities which produce a resonant electromagnetic field that causes charged particles to accelerate while also sorting protons into packets called bunches. Superconducting magnets kept at 1.9 K are left in charge of bending and reshaping the beam transversely: of these there are lattice magnets consisting of dipoles that bend the beam around the collider, and quadrupoles which
Figure 2: The CERN accelerator complex. Here shown is the LHC and its injector chain: the LINAC, followed by the PSB, the PS, and the SPS.

compress it vertically and horizontally; and insertion magnets which are placed right before the collision point and provide additional tightening of the beam to ensure high quality collisions.

1.2.2 The ATLAS Detector

The LHC provides collisions at various interaction points where the two opposite running beam pipes intersect. The collision events then need to be reconstructed at the detector level for new physics to be observed. A Toroidal LHC ApparatuS (ATLAS) is a general-purpose detector experiment at the LHC located in one of these interaction points. It consists of several layers of which each plays a role in the reconstruction of particle trajectories and particle identification. Starting from the collision point and going radially outwards:

1. The inner detector (ID) is closest to the interaction point and is subdivided into three components (moving radially outwards): the pixel detector, the silicon microstrip trackers (SCT), and the transition radiation tracker (TRT). The entire ID is immersed in a solenoidal magnetic field which causes charged particles to bend, and so the ID
provides vertexing information for tracks in the detectors, and allows measurements of direction, charge, and momentum of electrically charged particles produced in the collisions. [3]

2. The calorimeters follow next, and are situated outside the solenoidal magnet that surrounds the ID. The calorimeters measure the energy of particles by absorbing it, and they come in two types: the EM calorimeter which measures the energy of particles that interact electromagnetically, and the hadronic calorimeter, which measures the energies of particles that interact through the strong force but pass through the EM calorimeter (i.e. hadrons). These energy measurements are done by measuring the current produced from the ionization of the Liquid Argon (LAr) in between the metal layers that constitute the calorimeter and absorb incoming particles creating lower energy particle showers. [4]

3. Most particles with the exception of muons and neutrinos are absorbed either in the ID or in the calorimeters. The outermost layer of ATLAS is the muon spectrometer and serves the purpose of then tracking and measuring the momentum of those muons that passed through the inner layers of the detector. [5]

Figure 3 shows a diagram of the ATLAS detector.

![Diagram of the ATLAS detector](image)

Figure 3: The ATLAS detector. Going radially outwards, it contains the inner detector, the EM and hadronic calorimeters, and the muon spectrometer.
The search for rare BSM physics processes is reliant on having large amounts of “good” data to analyze. The amount of recorded data in ATLAS is given by the integrated luminosity $L$, given in units of inverse “barns” $b^{-1}$:

$$L = \int L dt$$

Here $L$ is the instantaneous luminosity, quantifying the rate at which particles are brought to collide, while the integrated luminosity measures the number of events over time. During Run 2, ATLAS collected approximately 139 fb$^{-1}$ of usable data. The events in this dataset are then reconstructed by analyzing tracking information from the ID and energy deposits in the calorimeters. This data provide the backdrop for physics analyses such as the one described in the next section.

2 **Anomaly Detection in $Y \to XH$**

2.1 $Y \to XH$

2.1.1 Overview

Section 1 of this paper briefly comments on some of the imperfections of the SM, and in such the motivation to look for BSM physics in the experimental front. Current theoretical predictions imply the existence of new physics at energy scales reachable by the LHC, and key extensions to the SM predict the existence of heavy diboson decay channels, where some new heavy particle (resonance) decays to two massive bosons and motivates searches for particles at the TeV scale. Since the Higgs boson couples to mass, it’s natural to assume that these new heavy objects would have decay channels that include a Higgs. This motivates a generic search for a new charged boson $Y$ at the TeV-scale, decaying to a SM Higgs and a new boson $X$. The Feynman diagram for this process is shown in figure 4.

The $Y$ and the $X$ in this search are assumed to be completely generic particles to allow for a *model-independent* search, despite theoretical motivations. Neither of the particles’ masses is known, and the aim of this search is to find an excess in the reconstructed mass of the $Y$ by scanning a two dimensional space of the potential $X$ and $Y$ masses. Figure 5 shows the current grid of Monte Carlo simulated mass points, or “signal grid”, which is later interpolated more finely to fill in for missing signal points.

This search was conducted before with a 36.1 fb$^{-1}$ dataset, here referred to as the “old analysis” [6], while the current search aims improve the tools for identifying the Higgs and the $X$, while utilizing the full Run 2 139 fb$^{-1}$ dataset. Here the Higgs is assumed to decay...
**Figure 4:** Feynman diagram for a generic particle $Y$ decaying to an $X(\to q\bar{q})$ and $H(\to b\bar{b})$ bosons.

**Figure 5:** Current simulated signal points for $Y \to XH$ in the 2D space of $m_X$ and $m_Y$, referred to as the signal grid.

into a pair of $b$-quarks, which is the Higgs' largest branching ratio at 58% [7], while the $X$ was previously assumed to decay to two light quarks. This is still the primary assumed decay mode of the current analysis, although the subject of this paper studies the introduction of a tool that allows the analysis to be sensitive to other hypotheses and be even more model-independent.
2.1.2 Boosted Jet Topologies

The mass of the Higgs is known to be approximately 125 GeV, while we assume the mass of the $Y$ to be in the TeV scale, and that of the $X$ of $\mathcal{O}(100)$ GeV. Energy conservation then implies that in a collision where a $Y$ is produced, its mass energy will go into producing both the $X$ and the Higgs, and the rest into their momenta. These two bosons are then correspondingly produced with very high momentum, and are in turn Lorentz boosted or just “boosted”. This further implies that the decay products coming from the $X$ and the Higgs are collimated, which produce an interesting topology in the analysis final state: the quarks produced from these particles cannot be detected on their own due to quark confinement; instead, they undergo a process of hadronization where hadrons (composite particles made of two or more quarks) are produced from the resulting quarks. These hadrons deposit energy in the hadronic calorimeter, which along with tracking information allows for their reconstruction as objects called “jets”. Each quark produced will hadronize to form a jet which is usually reconstructed with a small-radius parameter (small-R jets). In the case where the produced quarks are highly boosted, the average separation between the decay products is small, and instead of reconstructing the products from each quark as individual jets, a single jet with large radius parameter (large-R jets) is constructed. This is done in order to regain sensitivity to highly boosted events, and it is assumed that in $Y \to XH$ the final state of the analysis is two large-R jets coming from the $X$ and the Higgs. A schematic of how small-R jets are reconstructed as large-R jets is shown in figure 6.
2.1.3 Jet Tagging

Hadronic matter dominates the products of proton-proton collisions, and in turn other processes may generate jets that correspondingly become background for $Y \rightarrow XH$. The Quantum Chromodynamics (QCD) processes that lead to the production of jets are referred to as multijet processes, which here lead to the multijet or QCD background. These background processes dominate the data collected at the LHC, and so to enhance the sensitivity to rare, BSM physics, certain procedures need to be implemented to separate multijet background from signal events, a process called “tagging”. For jets coming from $H \rightarrow b\bar{b}$, a neural network is implemented that outputs a score determining the likelihood of an event being a Higgs event [8]. The studies to follow however focus on tagging the jets coming from the $X$.

In the old analysis this was done by exploiting the substructure of the large-R jets produced from the $X$: the old assumption was for the $X$ to decay to a pair of boosted quarks, which when reconstructed as a large-R jet would have a two-pronged substructure, corresponding to the energy deposits of each small-R jet. Multijet processes in contrast tend to generate jets that have a fairly homogeneous energy deposit, and so lack any meaningful substructure. $X$ jets were then separated from background events by analyzing their substructure – this was done using a variable called $D_2$, which quantifies the likelihood of a two-prong topology. However, the current analysis aims to be sensitive to various substructure hypotheses instead of solely two-pronged to improve its reach as a probe for BSM physics and model-independence. For these varying hypotheses, the usage of $D_2$ as a discriminant is suboptimal. The studies to follow evaluate the implementation of a new tool in $Y \rightarrow XH$ based on the principle of anomaly detection by introducing a Variational Recurrent Neural Network (VRNN)-based “anomaly score”. The implementation of the anomaly score should make the analysis sensitive to not only two-prong, but also various other jet substructures.

2.2 Anomaly Detection

Anomaly detection refers to the identification of anomalous elements in an otherwise homogeneous dataset. This can be done in a machine learning context by implementing a model that learns the most salient features of a dataset and can then identify anomalous data points solely on how poorly they are represented by the underlying learned distribution. [9] In practice, this is done by implementing a neural network that encodes the most prevalent features of data into a lower dimensional “latent space”, and is also able to decode or sample that latent space to reconstruct its inputs. This is shown in figure 7. The difference between the reconstructed output of the neural network and its input is quantified by a “loss” function, which can take various forms. The loss is typically designed such that outputs vastly
different from the network’s input have a high loss. In learning the features of a dataset, the neural network attempts to minimize its loss function and hence the reconstruction error.

![Neural network](image)

Figure 7: Neural network that encodes a dataset’s prevalent features into a latent space, and reconstructs its input by decoding, or sampling that latent space. Two prominent architectures that allow for this are the autoencoder and the variational autoencoder [9]

After training, one can then pick out anomalous data points by analyzing the network’s loss: a trained network will be able to reconstruct data points resembling “average” data well, yielding a small loss. While anomalous, out-of-distribution points will be poorly reconstructed and yield a large loss. The loss of the network can then be used as a discriminant for anomalous points in a dataset. The introduction of anomaly detection to high energy physics analyses such as $Y \rightarrow XH$ requires the implementation of a variational recurrent neural network (VRNN). The VRNN is a recurrent neural network (RNN) which contains a variational autoencoder (VAE), one of the more popular anomaly detection architectures, in its encoder-decoder step. [9] The main desired feature of the VRNN is that it allows for variable length inputs; this allows the VRNN to be trained over LHC data by modeling that data as a set of jet constituent four-vectors which often vary in length. As a result, one can use the VRNN’s loss function to define an anomaly score (AS), which can separate homogeneous, background jets from jets with substructure. The anomaly score is defined in terms of the Kullback-Leibler (KL)-Divergence of each jet constituent, averaged over the whole jet, given by: [9]

$$\text{Anomaly Score} = 1 - e^{-\frac{D_{KL}}{2}}$$

2.3 Performance of Anomaly Score in $Y \rightarrow XH$

For the studies to follow, the VRNN was trained over the full Run 2 dataset, although these results were evaluated in a 36.1 fb$^{-1}$ slice of that data. An AS was determined for each event of three $Y \rightarrow XH$ simulated signal points, as well as three “special” signal points representing various substructure hypotheses. The former represents two-prong substructure hypotheses, while the remaining three represent heavy flavour ($b$), three-pronged, and dark
jets. This allows for performance studies of the AS over the $Y \rightarrow XH$ datasets, as well as to test its model-independence. The full list of samples is as follows, with special samples shown in blue:

- HVT_Agv_VcXH_qqqq_m2000_m160 ($m_Y = 2000, m_X = 160$)
- HVT_Agv_VcXH_qqqq_m3400_m400 ($m_Y = 3400, m_X = 400$)
- HVT_Agv_VcXH_qqqq_m5000_m200 ($m_Y = 5000, m_X = 200$)
- Py8_A0_HZ_bbbb_M3000_m200_m400 (CWoLa RD; heavy flavor)
- Py8_Wprime_WZqqqqqq_M3000_m200_m400 (CWoLa RD; 3 prong)
- DJ_ModelA_3500_1jetFilter (dark jets) ($Z' \rightarrow$ non resonant dark quarks)

2.3.1 Training Performance

A selection on data events was applied before training, requiring the leading transverse momentum ($p_T$) jet to have $p_T > 1.2$ TeV and the total reconstructed mass from the $X$ and $H$ jets ($m_{JJ}$) to be $m_{JJ} > 1.3$ TeV. These selections were chosen for performance-related reasons, and limit the AS to having its optimal performance in the very boosted regimes. These selections are subsequently applied in the remainder of this evaluation. The training for the VRNN is unsupervised, and this study evaluates from epoch 57. The input characteristics of the corresponding $Y \rightarrow XH$ and special signals are shown in figure 8.

The performance of the model over these samples is given by the Receiver Operating Characteristics Area Under the Curve (ROC AUC) curves shown in figure 9. These curves contrast the performance of AS to $D_2$, as well as Tau32, the corresponding three-prong substructure quantifier. It is expected for the AS to not outperform $D_2$ and Tau32 in their subsequent regimes, although of importance here is the AS being the best discriminant for dark jets, which neither of the other variables is sensitive to.
Figure 8: Mass, $p_T$, $D_2$, and Tau32 distributions for the various signals the VRNN was evaluated over after training. In the left hand side are the $Y \rightarrow XH$ signal, while the right hand side shows the “special” signals.
Figure 9: ROC AUC curves contrasting the anomaly score’s performance to $D_2$ amd Tau32. The greater the area under the curve, the better the performance.
2.3.2 Analysis Performance

The remaining of this study devotes to analyzing the AS performance at the analysis level. This implies searching for an optimal cut in AS that allows for an enhancement of signal with respect to background, here taken to be data as the VRNN is evaluated over the Run 2 dataset. This implies the need to be careful about keeping the study blinded: the analysis has three distinct mass regions, one corresponding to the mass of the Higgs, ranging from 75 GeV to 145 GeV; while the other two correspond to a low mass band, 50 GeV to 75 GeV, and a high mass band 145 GeV to 200 GeV. The signal region is included within the Higgs mass region, and so to blind the study, the shape of data is taken from the high mass band validation region, and rescaled to match the entire data yield to the 36.1 fb$^{-1}$ dataset. This keeps the study from looking at data in a high AS bin. All other signals are also scaled to match 36.1 fb$^{-1}$.

The metric used to quantify the significance of signal is $S/\sqrt{B}$, where $S$ is the number of signal events, and $B$ is the number of background events. The optimal cut in AS is determined by picking an AS greater than cut that maximizes the sensitivity. This is shown in the plots in figure 10. The distributions of AS are plotted in the top panels for the $Y \rightarrow XH$ and special samples. The bottom panel plots the significance given by applying an AS greater than the bin value. To keep the evaluation in the optimal significance for both the $Y \rightarrow XH$ and special samples, an AS cut of $AS > 0.4$ was chosen.

Figure ?? shows the distributions of $m_X$ and $m_{JJ}$ before and after the AS selection. Of importance is that the ratios between the two distributions are fairly flat, with the exception
of the low $m_X$ regions. This implies both that a cut on AS does not produce a spurious signal, and that AS is not strongly correlated to either of the mass variables. This is an advantage with respect to $D_2$ and Tau32, which correlate strongly to mass.

The signal samples were then injected into the background distributions to evaluate the enhancement of signal over background after the selection. The distributions before and after the AS selection are shown in figures 12 and 13 respectively. The signal, background, and signal injected background distributions are plotted in the top panel, while the bottom panel plots the significance bin by bin. The enhancement is evaluated by computing the percent increase in significance after the selection on AS. Across the three $Y \rightarrow XH$ samples, there’s a $\sim 5$-20% increase in significance, and $\sim 5$-15% for the special signals. Figure 14 further shows the increase in significance across the entire $Y \rightarrow XH$ signal grid. The AS yields a significance increase of $\sim 5$-30% across the boosted ($m_Y \gg m_X$) samples, while there’s a drop in performance for the remaining points in the grid. This is expected both due to the initial training requirements of the VRNN, and due to the less prominent correlations between constituents in large-R jets outside the very boosted regime – the AS is designed to be a discriminant for boosted points.
Figure 12: “Bump hunt” plots before AS selection. The top panel shows signal, background, and signal injected background, while the bottom panel shows the significance plotted bin by bin.
Figure 13: “Bump hunt” plots after AS selection. The top panel shows signal, background, and signal injected background, while the bottom panel shows the significance plotted bin by bin, with the percent increase computed with respect to the maximum significance in the distributions before the AS selection.
Figure 14: Percent increase in significance of signal across the entire set of $Y \rightarrow XH$ simulated points. The percentage increase is computed from a similar procedure as shown in figure 13.

### 2.3.3 Conclusions

The studies presented here show that a selection on AS increases the significance of a signal with respect to background by approximately 5-30% for various substructure hypotheses. This presents the AS as a valid model-independent discriminant to be used in the $Y \rightarrow XH$ analysis that allows for sensitivity to multiple substructure hypotheses aside from two-prong substructure, and hence provides additional avenues to probing BSM physics. These results motivate the introduction of a new AS-based discovery region in the analysis that is sensitive to many kinds of new physics produced with a Higgs. To our knowledge, this is the first fully unsupervised method application to an ATLAS analysis. Some obvious next steps are to utilize the full Run 2 dataset in this study, as well as design a background estimation for this new AS region.
3 FEB2 Upgrades of the ATLAS Detector

3.1 The HL-LHC

The role of instrumentation in BSM physics searches is briefly highlighted towards the end of section 1, with emphasis towards the need for high luminosity to detect these rare processes. Currently the LHC has a peak instantaneous luminosity of $L = 10^{34} \text{ cm}^{-2} \text{s}^{-1}$, with a total of 139 $\text{fb}^{-1}$ of data being delivered during Run 2. To sustain its discovery potential, upgrades to the LHC have been proposed to increase its instantaneous luminosity by a factor of 5 and its integrated luminosity by a factor of 10 by 2026: the so-called “High Luminosity” LHC, or HL-LHC. The HL-LHC is expected to yield approximately 4000 $\text{fb}^{-1}$ of data in its first 12 years of running. The simultaneous interactions events observed by the detector are referred to as “pileup”, with the current LHC providing on average approximately 36 interactions per proton bunch crossing, while the HL-LHC expects up to 200 interactions on average. This high pileup environment will challenge the current ATLAS readout system in the LAr calorimeter; to account for both the increase in pileup and the subsequent need for higher radiation tolerance, the entire readout system at ATLAS is to be redesigned and replaced, in what’s referred to as the LAr Phase-II upgrade. [10]

The LAr calorimeter provides primarily EM calorimetry, with some hadronic calorimetry in ATLAS. These EM calorimeters are comprised of accordion-shaped copper-kapton electrodes placed between lead plates, immersed in LAr. [10] The ATLAS LAr calorimeter system is shown in figure 15. Particles passing through the calorimeter are captured by the metal layers and converted to showers of lower energy particles which ionise the LAr, generating a current that is measured by the readout electronics. The main component of the front end (FE) readout electronics are the front-end boards (FEBs), which are designed to both readout and digitize the LAr signals to be sent off the detector. Figure 16 shows the current ATLAS readout electronics, with the FEB highlighted. One of the components of the LAr Phase-II upgrade is upgrading the FEBs to accommodate the specifications of the HL-LHC, with new boards, FEB2, being designed to replace the current FE readout system. These FEB2 are developed and tested at Nevis Labs, Columbia University.

A diagram of the readout system, highlighting the FEB2 components is shown in figure 17. Each FEB2 board will contain 128 calorimeter channels, with a total of 1524 boards required to read out the entire LAr system. [10] A set of LAUROC preamplifier/shaper chips will perform both amplification and analog processing on the LAr signals. The output of the LAUROCs are then digitized by the COLUTA analog to digital converter (ADC) chips, which then outputs the signals as 16-bit words at 640 Mbps. Lastly, lpGBT chips serialize and repackage the ADC outputs into a single bit-stream to be sent off-detector.
Figure 15: The ATLAS LAr calorimeter system. Highlighted is the accordion structure of the EM calorimeter that is bathed in the liquid argon.

Figure 16: The current readout electronics in the ATLAS detector. Highlighted in the blue box is the schematic for the current front-end boards. These boards read in calorimeter data and digitize it to be sent off the detector.
3.2 Slice Testboard

The initial testing of the new FEB2 boards was done through the development of an analog testboard in 2019, containing 2 LAUROCs, 2 COLUTAs, and 1 lpGBT chip. The analog testboard was used to demonstrate and test the full readout chain of the FEB2 boards. To evaluate multi-channel performance, a slice of the final FEB2 boards was developed in 2020 having the same chip density and layout as the final boards: the slice testboard or sliceboard. The sliceboard integrates up to 8 LAUROC, COLUTAs, and lpGBT chips, and is capable of reading out up to 32 LAr channels. An image of the sliceboard is shown in figure 18. A graphical user interface (GUI) has been developed for the sliceboard, which allows for full board control and readout: the GUI allows for the calibrating, configuring, and reading back all the chips in the sliceboard, as well as providing a framework for data taking; it also provides a framework to determine the clock parameters for the chips in the board, under a procedure here referred to as a “clock scan”. A screenshot of the current version of the front page of the GUI is shown in figure 19. There is a lot of work being done in parallel to what is presented here, although the remainder of this section is devoted towards the development and implementation of a clock scan framework in the GUI.
Figure 18: The slice testboard, or sliceboard. The board contains the same chip density and layout of the final FEB2 boards, but with only 32 instead of 128 channels. Hence it is a slice of the final boards.

Figure 19: The startup page of the GUI. It contains buttons to write and read from the various chips in the board, as well as perform the clock scan procedure.
3.2.1 Clock Scan

Each of the COLUTA chips has 8 channels which map to different registers in the lpGBT chips. Determining appropriate clocking configurations is motivated by the fact that the timing settings between the COLUTA and lpGBT chips need to match for data to be read out correctly from the board. There are three parameters that need to be adjusted by the clock scan:

1. INV/Delay640: a global-level COLUTA delay parameter (i.e. applies to the entire COLUTA chip) that adjusts when the chip outputs data in 640 MHz ticks

2. xPhaseSelect: a channel-level COLUTA strobing parameter that determines when data is written to the lpGBT chips in picosecond time steps

3. lpGBT phase: a register-level lpGBT parameter that determines phasing for when the lpGBT reads in data. This parameter adjusts the framing of the data at the lpGBT level

All the above parameters can take upwards of 16 possible values. The clock scan procedure is set up such that the scan tests each possible timing combination for the INV/Delay640 and xPhaseSelect parameters, and uses this information to find an appropriate lpGBT phase parameter. This is possible because each COLUTA chip/channel combination has a unique serial pattern. Placing the board in serializer mode then causes it to output this serializer data which can be used to validate the timing. This is done by analyzing at each step of the clock scan how much the serializer data read from a given COLUTA channel is phase shifted from its known value. The phase shift is used to determine the lpGBT phase necessary for correct data reading given a combination of the INV/Delay640 and xPhaseSelect parameters. If the data read out does not match to a phase shift of the serializer pattern, the data is labeled as invalid. A set of tables output from the clock scan procedure is shown in figure 20. Here the columns represent different xPhaseSelect values, while the rows represent varying INV/Delay640 settings. The actual contents of the table correspond to the lpGBT phase determined from the phase shifts of the serializer pattern. Negative values in the table correspond to invalid serializer data. The clock scan tables then show all the possible combinations of clocking parameters for the lpGBT and COLUTAs that allow for correct data readout.

The actual clock configuration is then selected from this table by taking into account both that the INV/Delay640 parameter must be the same for all channels in a given COLUTA, and also that since the delay parameters are in the order of picoseconds, the timing
Figure 20: Outputs of the clock scan. These tables show which lpGBT phase parameter yields valid data given a combination of INV/Delay640 and xPhaseSelect parameters. These results are for COLUTA 17 in the sliceboard.
Figure 21: The score map and chosen clocking configuration determined by the algorithm implemented in the clock scan. The INV/Delay640 parameter chosen is applied to the entire COLUTA, while the remaining xPhaseSelect and lpGBT phases are determined such that small fluctuations in the xPhaseSelect timing do not change the needed lpGBT phase setting.

Parameters of the chips are subject to small fluctuations; so an optimal clock parameter is one that is immune to small fluctuations causing invalid data readout. What this means in picking an optimal parameter is that the configuration chosen must be surrounded by configurations with the same lpGBT phase parameter, so in case there exists a fluctuation in say, the xPhaseSelect, the lpGBT phase chosen will still work to read out good data. This is implemented through an algorithm that picks out “islands” of similar lpGBT phase data points, and searches through the clock scan result of each channel in a COLUTA for a given INV/Delay640 parameter that works at the chip level for every channel. It then picks an xPhaseSelect parameter based on regions with similar lpGBT phases. The algorithm does this by giving each point in the clock scan table a score, and then outputting an analogous table and picking out a configuration with the highest score given the above constraints.
One set of these tables is shown in figure 21.

Once these constants are determined, the clock scan framework is designed to rewrite the configuration files for the sliceboard, and in so doing implement the found clock parameters. Part of this framework also includes a checker that validates if serializer data is being correctly read out from the board, and in turn validates the results of the clock scan, aside from being a useful debugging tool.

3.2.2 Conclusions

This subsection described the basic features of the slice testboard and of the clock scan procedure. The clock scan is but one of the many features of the GUI, and only a small subset of the total work that goes into the development of the sliceboard. It however shows that the board can be properly configured with the correct clocking parameters, and later validate those parameters with the serializer data checker. Much work still needs to be done in the clock scan and other areas of the board. One such area is implementing a feature in the clock scan that allows it to determine valid clock parameters for both 16 and 32-bit modes of the sliceboard, which in turn are directly applicable to the calibration procedure of the multiplying digital to analog converter (MDAC) and successive approximation register (SAR) components of the COLUTA chips. More broadly, ongoing currently is the development of a new version (version 4) of the COLUTA chip, with the goal of having it implemented in a full 128 channel prototype FEB2 board by next summer.

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5 References


