

Monitoring of the ATLAS Liquid Argon calorimeter

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Abstract. The ATLAS detector at the Large Hadron Collider is expected to collect an unprecedented wealth of new data at a completely new energy scale. In particular its Liquid Argon electromagnetic and hadronic calorimeters will play an essential role in measuring final states with electrons and photons and in contributing to the measurement of jets and missing transverse energy. Efficient monitoring of data will be crucial from the earliest data taking onward and is implemented at multiple levels of the read-out and triggering systems. By providing essential information about the performance of each partition and its impact on physics quantities, the monitoring will be crucial in guaranteeing data to be ready for physics analysis. The tools and criteria for monitoring the Liquid Argon data in the cosmics data taking will be discussed. The software developed for the monitoring of collision data will be described and the results of monitoring performance for data obtained from cosmics data will be presented.

1. Introduction

The ATLAS Liquid Argon (LAr) calorimeter is one of two detectors used for calorimetry in the ATLAS experiment. The LAr calorimeter is a sampling calorimeter using cryogenically liquified noble gas as the active medium. The other system used for calorimetry is a scintillating tile calorimeter. Because of the high radiation-resistance of a noble gas system compared to scintillating tile, the LAr calorimeter is used for electromagnetic measurements, forward calorimetry, and also for the hadronic measurements in the endcap regions where high radiation renders a tile system infeasible. The tile system performs hadronic measurements in the barrel region [1].

The LAr calorimeter is divided into several partitions. In the electromagnetic partitions, the LAr calorimeter is notable for a unique accordion geometry that aids hermetic coverage by minimizing cracks. In the hadronic end-caps a more traditional plate geometry is used. In the forward calorimeters the electrodes form narrow, cylindrical channels filled with liquid argon around electrode cores, which reduces ion drift time and build-up [1, 2, 3]. See Fig. 1 for examples of each sub-detectors architecture.

The LAr calorimeter in total has 182,468 channels to be read-out and a collision frequency of 40 MHz, posing a considerable challenge to monitoring, read-out, and data storage [3].

2. Operation

Like all sampling calorimeters, the signal measurements in the LAr calorimeter begin with ionization pulses in the individual cells of the calorimeter due to particle tracks. These pulses are sent (see Fig. 2) from the detector to the Front-End Boards (FEBs), where the analog signals

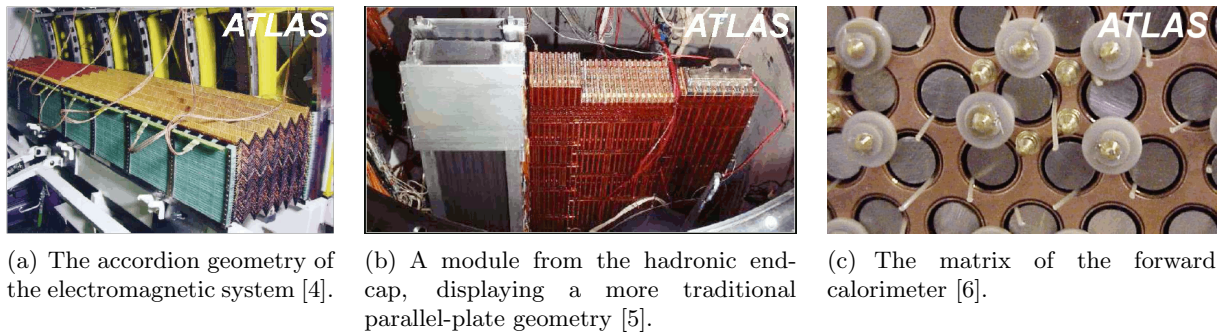


Figure 1. The various architectures used in segments of the LAr calorimeter.

are amplified and shaped. The FEBs sum the signals from the calorimeter cells into towers of size $\Delta\eta \times \Delta\phi = 0.1 \times 0.1$ for each layer in preparation for input to the Tower Builder Boards. The FEBs store the signal in on-board memory until the Level-1 trigger decides whether to keep or reject the event. If the event passes the Level-1 trigger the FEBs digitize the signals and pass them on to the Read-Out Drivers (RODs), while the analog signal is passed to the Tower Builder Boards [7].

In the electromagnetic segment Tower Builder Boards complete the analog sum of cells in order to construct trigger towers. These towers are transmitted to the Level-1 off-detector electronics for digitization. In the Hadronic End-Cap, Tower Driver Boards produce differential signals and pass them on to Level-1 [7].

The RODs receive the digitized signal from the FEBs and proceed to compute the energy for each channel, as well as the timing and a pulse shape quality measurement (χ^2). As shown in Fig. 3(a), the pulses produced in the calorimeter are triangular, but are shaped by the FEBs into a bipolar shape that is sent to the RODs. The bipolar pulse is sampled by the FEBs at intervals of 25 ns. Digital Signal Processors (DSPs) on the RODs reconstruct the signal and use the amplitude of the shaped pulse to calculate the energy. Due to the timing restrictions (Level-1 operates at 75 kHz) usually only 5 samples are taken of the pulse, timed to capture the region of the peak of the signal pulse, but as many as 32 samples can be taken. The samples from signals with energy greater than a threshold are stored in the event stream for later checks by monitoring algorithms. The RODs also monitor operations and parameters, such as the temperature of the electronics and busy signals. The resulting signal data is passed to the Level-2 trigger [3, 7]. The Level-2 trigger and the succeeding event filter construct more complicated physics objects

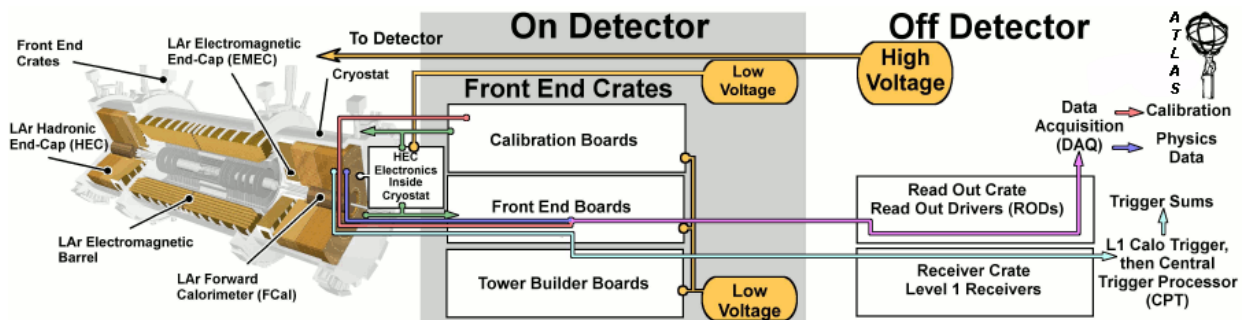


Figure 2. The flow of data in the ATLAS LAr detector [8].

from the signals.

The LAr calorimeter is also equipped with calibration boards used for testing the detector. During calibration, an electronic pulser is used to inject current into the calorimeter cells and provide a well-defined proxy for the actual physics signal. These benchmark pulses can then be used to calibrate the signal gain, as well as guarantee timing measurements with a resolution on the order of 1 ns, both of which are vital for producing precision energy measurements. Pedestals are also taken for the calorimeter cells during calibration, providing a benchmark for how the calorimeter responds when no signal pulses are present [3, 9].

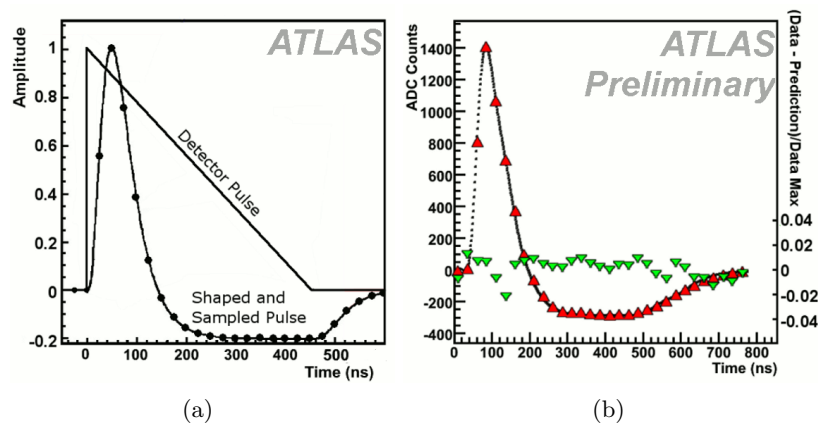


Figure 3. (a) The triangular signal pulse produced inside the calorimeter and the pulse used by the RODs after re-shaping by the FEBs. The peak in the re-shaped pulse is used to calculate the energy in each channel [2]. (b) A typical measurement in 32-sample calibration mode of a pulse shape from a 15 GeV cosmic-ray ($\blacktriangle$), compared to the predicted ionization pulse ($\bullet$). Also plotted is the fractional difference between measured and predicted ($\blacktriangledown$).

3. General ATLAS Online Monitoring Tools

ATLAS makes general monitoring tools available as part of the ATLAS online software package. In addition to online monitoring the package provides for control of data runs, configuration of the Trigger & Data Acquisition (TDAQ) system, and monitoring of the ATLAS infrastructure. The graphical user interfaces and information management that these tools require are also provided [10]. These tools provide a foundation for the sub-detectors to build upon. Each sub-detector of ATLAS, including LAr, calls on these tools to monitor calorimeter infrastructure and report on the data quality of runs. Examples of these general tools available in ATLAS include:

ATLANTIS/VP1: The ATLANTIS event display presents read-out information mapped to a simplified detector geometry. It has been used in commissioning, monitoring, and physics analysis. It is useful for identifying problem areas in detectors. An example of the display can be seen in Fig. 4(a), which shows a cosmic muon which passed through every barrel detector during cosmics commissioning. More information can be found in [11].

The Virtual Point 1 (VP1) event display is integrated into the ATLAS data processing framework and has direct access to the detector models used by reconstruction. A VP1 display can be seen in Fig. 4(b), showing an event from the September 2008 LHC start-up featuring the halo of outlier particles from a single proton beam striking the detector. More information can be found in [12].

Detector Control System (DCS): DCS monitors the hardware and infrastructure of each subsystem, as well as changing the hardware parameters and turning sub-components on and off. For each component important values, such as temperature, current, and voltage can be displayed and their trends plotted. DCS also categorizes, collects, and displays alarms from each sub-component, as well as alerting a central DCS monitor. For more information see [13].

Data Quality Monitoring Framework: ATLAS provides a standardized data quality framework. Each sub-detector provides custom algorithms which are used to analyze online data and flag the data based on its quality level, as well as pass on information useful for analyzing the source of the bad flag. In some instances the quality flagged could be so low as to require the cessation of running. These flags and analyses are used both during detector operations to monitor running and are also passed to the offline reconstruction as a check on which information needs to be re-evaluated and which is good for physics analysis or is unusable [14].

Online Histogram Presenter (OHP): The Online Histogram Service is responsible for directing the flow of monitoring histograms from all sub-detectors and their component systems. The Online Histogram Presenter is the universal method for viewing monitoring histograms in ATLAS. The data is fed to OHP from dedicated processing tasks in the on-line software. OHP can collect and display all the plots produced by the LAr monitoring framework. Plots are also made available through internet-accessed web displays for preliminary offline analysis. For more information see [15].

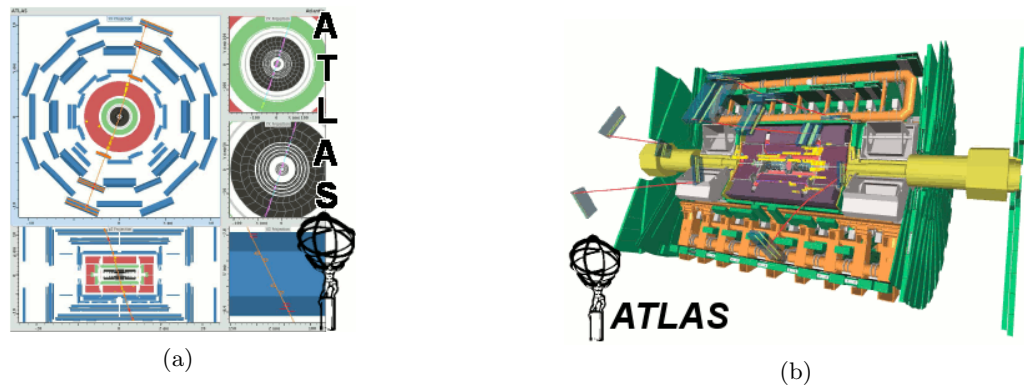


Figure 4. Examples of (a) the Atlantis event display showing a cosmic muon passing cleanly through the barrel of the detector; (b) the Virtual Point 1 event display showing a beam halo event from the LHC start-up in September 2008.

4. Online/Offline LAr Monitoring Algorithms

The online and offline monitoring algorithms of the LAr calorimeter are built on the ATHENA software framework, which is used by the ATLAS reconstruction algorithms, providing continuity and ease of use at all levels of monitoring and analysis. The Athena framework is derived from the LHCb's GAUDI framework, which provides basic libraries and tools for physics analysis. These algorithms also interact with the ATLAS Data Quality monitoring framework and provide the algorithms used to evaluate and flag the quality of the data. The tools are designed to study

the performance of the LAr calorimeter and ensure it does not deviate from that required to make accurate physical measurements. The LAr monitoring algorithms are summarized below.

High-energy digit algorithms

These tools provide information supporting the calculation of the energy from the samplings of the physics signal pulses.

- The algorithms calculate a cumulative average of signal sampling shapes for each partition of the calorimeter over each run, allowing a online users to check the rough timing calibration of the detector. An example of a one-run cumulative average signal shape in 32-sample mode is provided in Fig. 5(a).
- General tools are also provided to monitor for anticipated problems, such as saturated signals or null signals. The timing is also monitored for signals falling outside the defined timing window. In physics mode running, only five samples are taken. In order to properly derive the energy from the high-energy digits, these five samples must fall into the recorded timing window.

Data integrity algorithms

These tools provide information on whether the components of the calorimeter are functioning properly and to monitor the quality of the data stream for problems. Flags related to data quality are passed on to ATLAS run control and in the event of a serious data integrity problem, operation of the detector may be suspended.

- The algorithms retrieve information from the RODs such as the temperature and occupancy of the electronics.
- The algorithms monitor the electronics for anticipated problems, particularly in the FEBs. Many of these problems can prevent the FEBs from delivering data at all or result in corrupted data. The algorithms are highly important despite the rarity of the errors occurring.
- The algorithms provide checks on the high-energy digit calculation performed on the DSPs by performing a comparison calculation using the signal samplings passed on for certain cells meeting an energy threshold, as mentioned in the Operations section. Unexpected differences between the two samples are a clear indication of DSP malfunction.

Misbehaving channel algorithms

These tools provide monitoring of noise pedestals and variations in the calorimeter noise, as well as flagging dead channels or channels with malformed pulse shapes.

- Tools are included in this algorithm that perform general monitoring of the noise in the calorimeter against baseline pedestal values previously determined during the periodic calibration runs.
- Other tools are available that monitor for odd cells, such as those that exhibit noise falling outside of a predetermined range of the channel pedestal. For example, Fig. 5(b) shows for half of the electromagnetic barrel the percentage of events with an odd cell. A cell is odd if the initial sample of the high-energy digits exceeds a value greater than 3 times the calibrated pedestal level (σ_{noise}); if properly timed the initial sample should occur before any physics signal and thus should be near the pedestal of the cell. Each entry in the histogram is the percentage of odd events for each cell. The expected mean value is 0.27%, in agreement with the displayed performance. Monitoring this value over time allow the pedestal drift and noise variation to be observed. Fig. 5(c) shows a similar plot, only each entry of the histogram is the percentage of odd cells in an entire partition of the calorimeter for each event. This measurement is also expected to have a mean at 0.27% as gaussian behavior predicts. A shift away from the expected value can betray the presence of noise bursts, where odd cell noise occurs in numerous cells

at once. Such an effect is clearly absent from Fig. 5(c), which exhibits the expected behavior.

- Specialized tools are available to identify features and problems specific to cosmic-ray muons during the cosmic-ray commissioning phase.

Physics monitoring algorithms

These tools are being developed in collaboration with the ATLAS physics groups to monitor physics objects such as cell clusters and energy symmetry in the detector, as well as high level objects built from calorimeter measurements, such as measured particles.

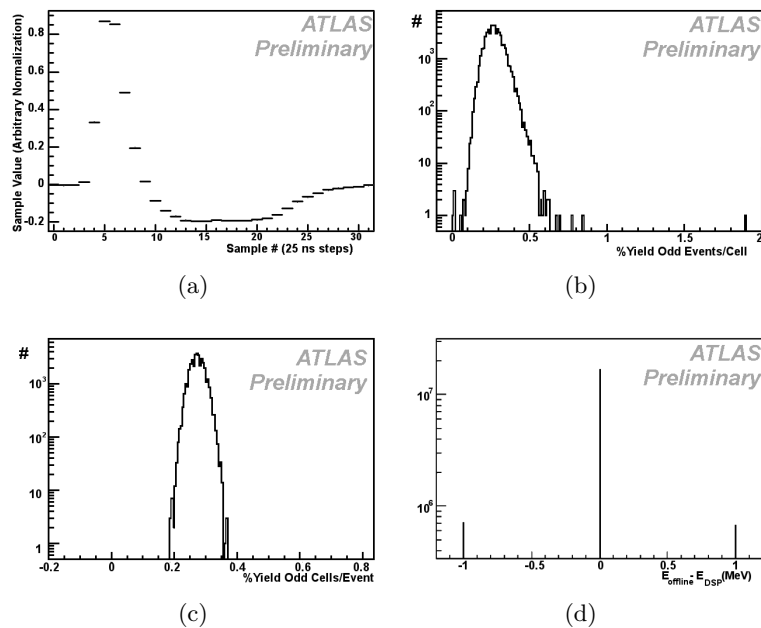


Figure 5. (a) shows a reconstruction of a 32-sample average of pulse shapes from half of the electromagnetic barrel, used to tune the timing of the LAr detector. (b) shows the percentage of events with an initial value greater than $3\sigma_{\text{noise}}$ for each calorimeter cell in half of the EM barrel. The expected mean value is 0.27%, which agrees with the result displayed. (c) shows the percentage of cells for each event which had noise above $3\sigma_{\text{noise}}$. Again, the expected mean value is 0.27% and agrees with the plot shown, which means that noise bursts are not present. (d) shows the difference between the energy calculation made by the DSPs and a calculation performed by offline algorithms using the high-energy digits; the outliers at 1 MeV fall within the expected accuracy range for the two methods (the histogram binning is 1 MeV).

During running, these algorithms are supplied by the LAr monitoring packages and operate in the ATLAS online software. They receive data from the TDAQ through dedicated monitoring computing farms and allow personnel in the ATLAS control room to monitor for data quality and other issues as the data is accumulated. For offline monitoring the exact same algorithms are provided by the LAr monitoring package and applied using the ATHENA framework. While final bulk processing of collected data, including detailed re-calibration of the detector response to physics objects, may take on the order of weeks to be completed and made available to individual users, the initial express stream is immediately available and is used by the LAr calorimeter group for offline monitoring (see Fig. 6), as well as for preliminary data quality checks. On the order of 10% of full data stream events are sampled by the TDAQ and recorded in the express stream. The express stream can then be used for offline monitoring and initial

calibration of the detector. Offline monitoring makes use of the same framework as ATLAS reconstruction, the aforementioned ATHENA framework. The focus of monitoring is the same as for online monitoring: high energy digits, data integrity, and misbehaving channels. For example, Fig. 5(d) plots the difference in the energy calculation between the calculation performed by the DSPs and a calculation performed directly from the recorded high-energy digits by the monitoring software. The example was performed offline, but the check can be made both online and offline. Some difference is to be expected, as evident by the outliers in Fig. 5(d), but it is important as a check on the DSP calculation process. The TDAQ also produces full trigger

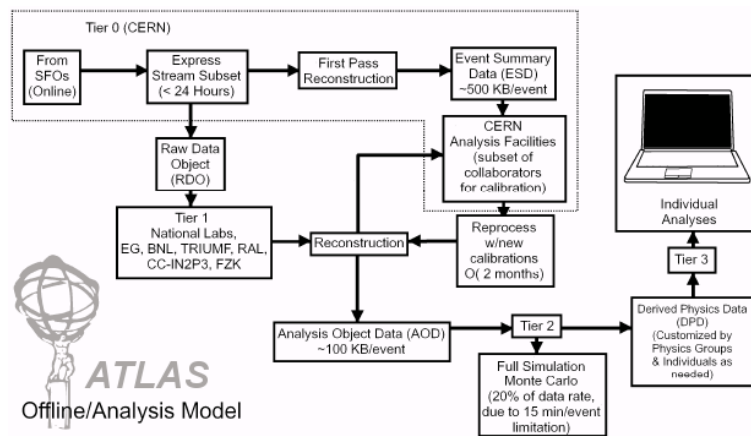


Figure 6. The plan for offline reconstruction and distribution of data in the ATLAS experiment [16].

streams that are stored for reconstruction as well as calibration streams containing partial event information used to calibrate the calorimeter (and other detector components). In turn these calibrations are used to reconstruct the trigger streams more accurately at a later date, as shown in Fig. 6. Beyond basic offline monitoring, the reconstructed data is used to examine the overall performance of the LAr calorimeter and monitor that its response conforms to expectation. Examples of results from more involved studies of detector performance and monitoring follow in the next section.

5. Selected Results

The ATLAS LAr calorimeter has been running cosmic-ray muon tests since 2007, allowing the LAr Group to perform more detailed monitoring and studies of detector performance. On behalf of the ATLAS LAr Group, selected results are presented here.

Fig. 3(b) shows a typical pulse from the LAr electromagnetic barrel obtained during cosmic-ray commissioning. The electronics were in the 32-sample calibration mode, allowing the full pulse shape to be captured. During normal physics running, only the first five samples would be taken, capturing the peak and allowing the energy to be derived from its amplitude. The data agree nicely with the predicted ionization pulse (within ~2%, due to uncertainty in the simulation), with the difference as a fraction of the maximum amplitude also plotted. The quality of the fit in the 500-700 ns range is attributed to ~150 micron shift in electrode position introduced into the prediction model. Note that the undershoot length (the region between 200 and 600 ns) is directly related to the drift time of the individual calorimeter cell producing the signal pulse and the rise of the undershoot region is related to the offset of the electrodes from their nominal spacing.

Fig. 7 presents the results of a study of drift time in 32-sample cosmic-ray events, using ~331769

signal pulses with an energy greater than 1 GeV in the middle sampling layer of the LAr barrel region ($|\eta| < 1.5$). The drift time and offset can be extracted from the undershoot region using a fit of the signal shape. In the figure, the color axis represents the number of re-weighted entries per η -drift time bin. They have been re-weighted to accentuate events with smaller fit errors on the drift time parameter, while keeping constant the total number of entries. The black bars are the mean values per η bin. The solid orange line is the predicted performance. We expect that the drift time will vary from the expected drift time due to variation in absorber thickness, shown in the plot varying against η . Comparison of the data to the prediction limits the η -dependent non-uniformity of the calorimeter response due to the gap variation to be no more than $0.320 \pm 0.007\%$.

Fig. 8(a) shows the cluster energy distribution for the two different cluster algorithms, the

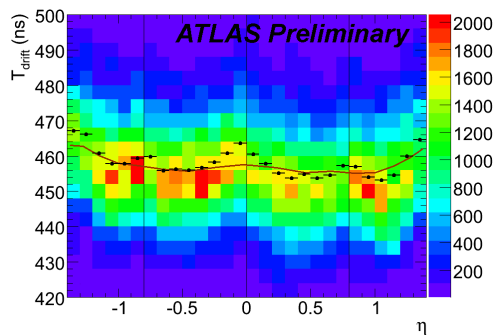


Figure 7. Drift times in the LAr barrel. The color index represents the re-weighted number of pulses per η -drift time bin. The black bars are the means of each η bin. The solid orange line shows the predicted performance.

topological LArMuID and the a 3x3 sliding-window cluster. See [17] for details of the two algorithms. LArMuID is not optimized for cosmic-ray events and is included in the studies as a benchmark [18]. The size of each cell in the cluster is $\Delta\eta \times \Delta\phi = 0.025 \times 0.0245$. The clusters are taken from events selected for passing near the interaction region and limited to the second sampling layer. The clusters in Fig. 8(a) were taken from the eta region $0.3 < \eta < 0.4$, but the energy distribution is characteristic for all η . The cluster energies have been fit with a Landau distribution convoluted with a Gaussian. The most probable value (MPV) of the energy of the LArMuID algorithm is less than that of the 3x3 cluster distribution due to the bias introduced from including only cells with energy above a certain threshold. The 3x3 cluster is of sufficient size to capture all of the relevant energy in cosmic-ray events, and the fitted gaussian-width is consistent with the non-correlated noise of the summed 9 cells [19]. Fig. 8(b) is a replication of the same analysis using cosmic Monte Carlo events. We can see that the cosmic-ray data is behaving as the Monte Carlo analysis predicts and provides a nice confirmation that our simulations accurately model the calorimeter.

The plots in Fig. 9 concern the uniformity of response of the LAr detector derived from measurements like the ones in the preceeding paragraph. A careful study of the uniformity of the calorimeters energy response is vital to accurately measure physics data and is the first step in correcting for any non-uniformity. Fig. 9(a) shows the MPV of the energy as a function of η , for the LArMuID and 3x3 Clusters compared to Monte Carlo. The relative depth of the second sampling layer is also shown for comparison. The energies and depths are normalized to their values at $\eta = 0.35$. The energy distribution shows the expected dependence of uniformity on cell depth to within 2% of our simulations [19]. Fig. 9(b) shows the same analysis performed using a 1x3 sliding-window cluster. This cluster should exhibit less bias than LArMuID by using a fixed cluster size, but also less noise than the 3x3 cell clusters due to the smaller size. However, a relatively small sample size limits this study, but shows promise at being an improvement over the 3x3 cluster.

Fig. 10 shows a preliminary study of the value of $|\Sigma \vec{E}_T|$ calculated by computing the

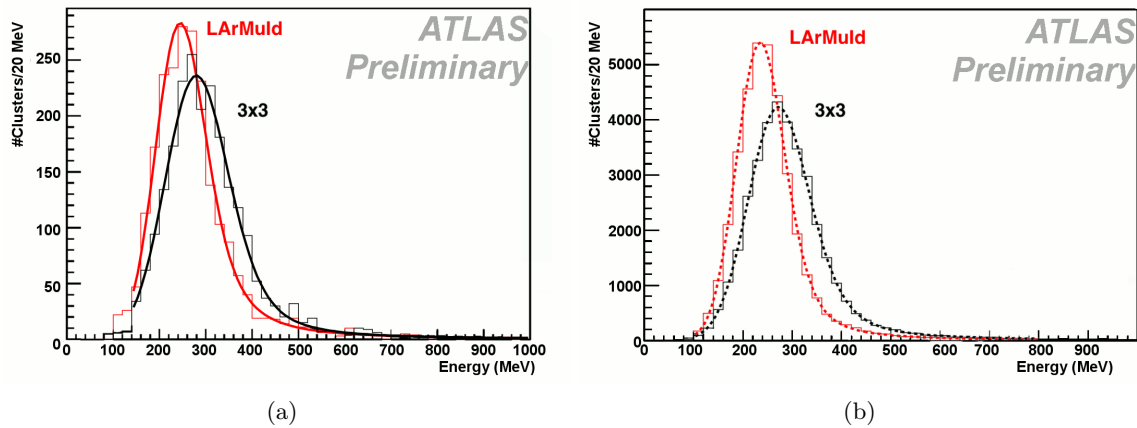


Figure 8. (a) A plot of the energy distribution of the LArMuID algorithm (red) and the 3x3 cluster algorithm (black). (b) The same plot using cosmic-ray Monte Carlo data. A comparison of the two plots demonstrates the accuracy with which our simulations model calorimeter performance.

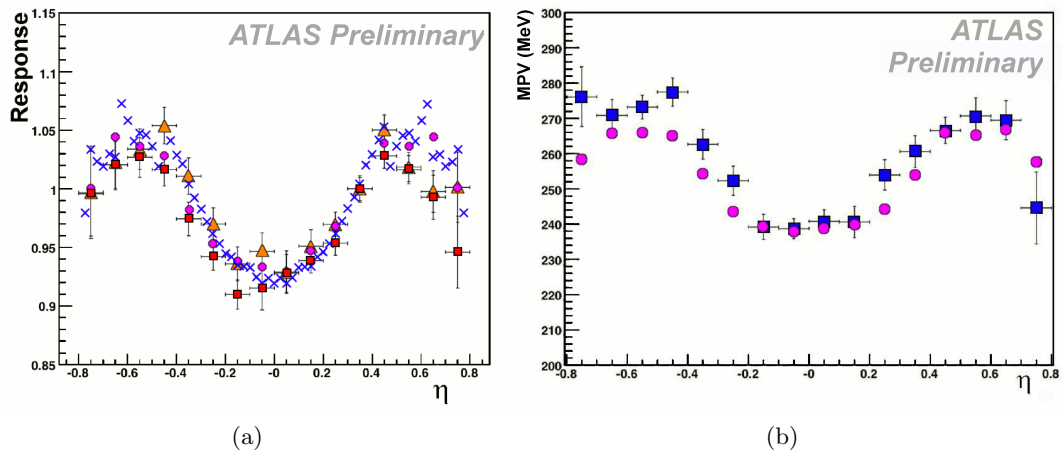


Figure 9. (a) A comparison of the LArMuID ($\blacktriangle$) and 3x3 Cluster ($\blacksquare$) algorithms and Monte Carlo. The relative cell depth of the second sampling layer ($\times$) is included. The y-axis (response) is the relative value of each plotted parameter (both energies and depth) normalized to its value at $\eta = 0.35$. Monte Carlo data ($\bullet$) is available for comparison. (c) The same plot using a 1x3 cell cluster ($\blacksquare$) and more limited sample size. The y-axis in this plot is the energy derived from the peak of the fitted Gaussian-convoluted Landau distribution. Monte Carlo data ($\bullet$) is available for comparison.

vector sum of the x - and y -components of $\vec{E}_T$ for each cell and taking the magnitude $|\Sigma \vec{E}_T| = \sqrt{(\Sigma E_x)^2 + (\Sigma E_y)^2}$. This was only done for cells having $|E| > 2 \cdot \sigma_{\text{noise}}$ above the noise. As expected, a random trigger tends to produce a cleaner plot that exemplifies the noise contribution in the detector. Data from the L1Calo trigger, which triggers on combined calorimeter events (such as electromagnetic showers, tau-jets, hadronic jets, or $\cancel{E}_T$ and $\Sigma \vec{E}_T$), shows the expected result from cosmic-ray events. A comparison of the noise to a toy model is included.

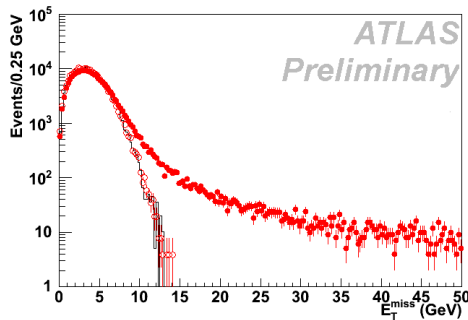


Figure 10. A plot of $|\Sigma \vec{E}_T| = \sqrt{(\Sigma E_x)^2 + (\Sigma E_y)^2}$ in the ATLAS LAr calorimeter for random triggers ($\circ$), the L1 calorimeter trigger ($\bullet$), and a toy Monte Carlo model (solid line). Only cells with $|E| > 2 \cdot \sigma_{\text{noise}}$ were selected.

6. Conclusion

The ATLAS Liquid Argon group makes use of a number of tools to efficiently monitor the Liquid Argon calorimeter and ensure proper running of the experiment. These tools are provided within the ATLAS online software and ATHENA analysis frameworks; common LAr algorithms are made available in both frameworks, ensuring continuity. Considerable effort has gone into preparing these monitoring tools for the LAr calorimeter, allowing the crucial parameters (high-energy digits, data quality, noise, and pedestals) to be carefully measured. These tools have been tested by both Monte Carlo data and cosmic-ray commissioning of the calorimeter and efforts continue to further develop them.

In addition to the standard monitoring tools, numerous and extensive analyses of the calorimeter performance have been performed, including preliminary efforts at understanding energy measurement performance, global energy measurements ($\Sigma \vec{E}_T$), and the drift time performance of the calorimeter. Such efforts make the ATLAS LAr Group well prepared for the eventual commencement of data taking.

7. References

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