

SIMULATION OF CDMSLITE DETECTOR'S RESPONSE TO ELECTRON RECOIL AND  
COMPARISON TO EXPERIMENTAL DATA

A Dissertation

by

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## ABSTRACT

Detectors consisting of a single germanium crystal and superconducting sensors have been shown to be sensitive to small energy deposits when placed under high voltages in cryogenic conditions such as in the Super Cryogenic Dark Matter Search (SuperCDMS) experiment. In this work, we compare simulations of interactions to the data from the low-ionization threshold experiment (CDMSlite) to improve our understanding of the dominant microphysical processes that occur billions of times before energy collection and signal readout. The simulations allow for quantitative macroscopic modeling of the detector response as a function of both time and interaction position which can be used to improve the sensitivity of the experiment. The results suggest that simulation-based methods may provide better rejection of poorly-measured events, that high-quality interaction position estimations are possible and that there may be problems with the current calibration procedures for the experiment. We find that there is qualitative agreement between the simulated and real data, which suggests that we are on the right track, but quantitative differences which suggests further improvements are necessary. We highlight the similarities and differences between simulated and real pulses to indicate the path forward for further improvements in both simulation fidelity and analysis.

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The contents of this work are solely the responsibility of the author and do not necessarily represent the views of the US DOE.

## NOMENCLATURE

|             |                                                                                                                                                                                                                       |
|-------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| ADC         | Analog-to-Digital Converter, a device or system that converts continuous analog signals into discrete digital numbers                                                                                                 |
| ADC Count   | The unit in which the discrete digital numbers of ADC output are expressed                                                                                                                                            |
| DetectorSim | Detector Simulation, a module within the SuperCDMS simulation infrastructure that simulates charge and phonon propagation in the detector and readout                                                                 |
| ER          | Electron Recoil, interactions caused by incident particles such as photons and electrons in which the electrons in the atoms of the crystal lattice are ionized                                                       |
| ESA         | The European Space Agency, a 23-member international organization devoted to space exploration                                                                                                                        |
| Fast Energy | The portion of the total phonon energy collected at early times at the surface of the detector after an interaction, defined in this work as within the first 100 $\mu$ s following an interaction or energy deposit  |
| GEANT4      | GEometry ANd Tracking 4, a software toolkit for simulating the interactions of particles within matter using Monte Carlo methods                                                                                      |
| NASA        | The National Aeronautics and Space Administration, an independent agency of the U.S. federal government responsible for the United States' civil space program and for research in aeronautics and space exploration. |
| NR          | Nuclear Recoil, interactions caused by incident particles such as WIMPs and neutrons in which the nuclei of atoms gains kinetic energy and 'kicks back'                                                               |
| NuMI        | Neutrinos at the Main Injector, a project at Fermilab which creates an intense beam of neutrinos aimed towards the Far Detector facility near Ash River, Minnesota for use by several particle detectors              |
| Phonon      | the quantum mechanical description of an elementary vibrational motion in which a lattice of atoms or molecules uniformly oscillates at a single frequency, which can be treated as a particle                        |

|               |                                                                                                                                                                                                                                                                                                                                                                                                               |
|---------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| QET           | Quasiparticle Trap Assisted Electrothermal Feedback Transition Edge Sensor, the composite superconducting tungsten and aluminum components which are operated at or near the superconducting region to take advantage of quasiparticle trapping and electrothermal feedback, which is instrumented on the top and bottom surfaces of the CDMSlite detector and used to collect phonons for energy measurement |
| Quasiparticle | a concept used to describe a collective behavior of a group of particles that can be treated as if they were a single particle. In a superconductor, the breaking of a Cooper pair by a phonon can be modeled as the creation of a pair of quasiparticles                                                                                                                                                     |
| SourceSim     | Source Simulation, a module within the SuperCDMS simulation infrastructure that simulates incoming particles and energy deposit response                                                                                                                                                                                                                                                                      |
| SuperCDMS     | Super Cryogenic Dark Matter Search, a series of experiments designed to directly detect interactions from dark matter where the detectors are operated at millikelvin temperatures                                                                                                                                                                                                                            |
| SuperSim      | The software framework that handle the simulation chain for the SuperCDMS experiments                                                                                                                                                                                                                                                                                                                         |
| Slow Energy   | The portion of the total phonon energy collected at late times at the surface of the detector after an interaction, defined in this work as after $100\ \mu s$ following an interaction or energy deposit, when phonons are uniformly distributed within the detector                                                                                                                                         |
| TES           | Transition Edge Sensor, the tungsten components of the QETs operated within the a small range of temperature (transition-edge) where its resistance can vary significantly due to a small change in temperature                                                                                                                                                                                               |
| WIMP          | Weakly Interacting Massive Particles, a hypothetical particle candidate for dark matter where the particle has mass and is assumed to interact via the weak force with a nucleus of a normal matter atom                                                                                                                                                                                                      |

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## 1. INTRODUCTION

There is significant evidence for the existence of a mysterious substance that constitutes approximately a quarter of the universe's mass-energy content, but does not emit, absorb or reflect light so that we cannot 'see' it directly. This unseen substance has been named dark matter. Additional evidence that it has a particle-like nature has motivated physicists to experimentally confirm that it is a particle and uncover its properties through various methods, primarily by observing its interactions, if any, with ordinary matter via forces other than electromagnetism.

In this context, the Super Cryogenic Dark Matter Search (SuperCDMS) experiments represent the state of the art in providing sensitivity to potential dark matter interactions via direct detection methods, leveraging semiconductor detectors and superconducting sensors at milliKelvin (mK) temperatures. One of the experiment modes, the low ionization threshold experiment (CDMSlite), aims to detect interactions from dark matter particles in the mass range of  $0.3 - 10 \text{ GeV}$ <sup>1</sup> that is predicted to deposit energy as low as a few dozen of eV when they interact. This thesis presents our work on simulating the response of the detector used in CDMSlite, referred to as the CDMSlite detector, to interactions and comparing the results with real experimental data. This approach aims to deepen our understanding of both the detector's performance and the underlying characteristics of the observed data to improve future analyses to enhance the possibility of discoveries as well as provide confidence in future results.

In the first chapter of this thesis, we describe the scientific motivation for the dark matter search, overview a dark matter candidate, outline the SuperCDMS experiment and CDMSlite detector, and describe our thesis goals. In Section 1.1, we overview the evidence for the existence of dark matter and its particle-like nature. In Section 1.2, we discuss a particular particle model for dark matter and one of the direct detection methods to search for it. In Section 1.3 we overview the SuperCDMS experiment that searches for dark matter particles, including the approaches,

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<sup>1</sup>We are using natural unit systems with the speed of light,  $c$ , set to 1. So, the mass unit  $\text{GeV}/c^2$  is written as  $\text{GeV}$  here.

principles, and objectives, along with the big picture of the CDMSlite detector physics and the expected interactions within it. In Section 1.4 we describe the goals of this work and outline the contents of each chapter in the rest of this thesis.

## **1.1 Evidence for the Existence of Dark Matter Particles**

The concept of dark matter began to take shape in the late 19th century and was explicitly mentioned in 1906, as new advances in technology allowed astronomers to observe ever fainter objects [1]. Today, it refers to matter that fills the universe but neither emits, absorbs, nor reflects light, rendering it undetectable through conventional electromagnetic methods. While there are many pieces of evidence that point to its existence and some of its properties, for pedagogical reasons in this section we focus on two sets of astronomical evidence supporting the existence of dark matter and another observation indicating its particle-like properties.

In the same way that the amount of light from the sun allows us to measure its mass, and that the theory of gravity allows us to predict the speeds of the planets based on that mass, similar observations and predictions can be made about groups of distant stars and galaxies. One set of astronomical evidence is the observation that the speeds of galaxies/stars are higher than what would be expected based on the amount of nearby mass inferred using the light emitted by visible matter. The earliest evidence was published in 1933 based on a combined set of observations of the Coma Cluster [2]. Stellar models were used to interpret the observed light distribution of the cluster to infer its mass distribution, which was then used in gravitational models to predict the speeds of galaxies within it. The galaxy speeds exceeded expectations by more than 2000 km/s suggesting that there was a large amount of unseen matter in the cluster. Similar phenomena are observed in the speeds of stars, as summarized in Section IV of Ref. [1], as they orbit within a galaxy at various distances from the center, known as a rotation curve. Figure 1.1 shows the discrepancy between the observed rotation curve of the visible objects in the M33 Galaxy and the curve expected solely based on the mass of the visible matter [3, 4]. The gap between them can be explained by the presence of dark matter

A second set of astronomical evidence comes from light traveling from distant sources towards

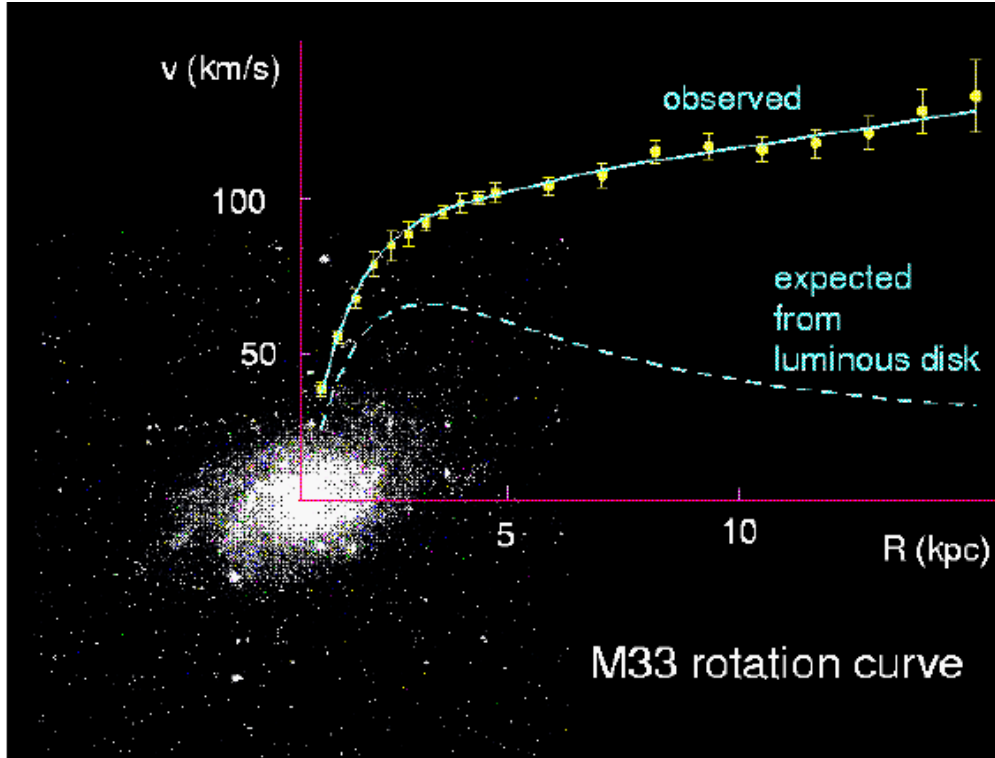


Figure 1.1: This figure shows the orbital speeds of visible objects in the M33 Galaxy as a function of their radial distances from the galaxy’s center based on observation (yellow dots) and expectations from the gravitational pull due to visible matter only (dashed line). We show it because the significant discrepancy between observations and expectations provides evidence for the existence of unseen mass filling the galaxy. The solid line is the best-fit for a model that includes a distribution of a large amount of matter that isn’t seen directly, known as dark matter. Figure is downloaded from Ref. [5] which is cited from Ref. [4]. Curves are originally from Ref. [3].

the Earth, but has had its path changed, or bent, by mass along the way. According to general relativity, the path of light is effectively bent when it passes near a massive object due to the curvature of spacetime caused by the object’s gravity, a phenomenon known as gravitational lensing [6]. The degree of lensing is proportional to the mass distribution of the intervening object. An example is illustrated in Figure 1.2a, where we show the scenario of two galaxies, labeled ‘far’ and ‘near’, both of which emit light. As the light from the far galaxy traverses space, its path is bent by the gravitational influence of the mass in the near galaxy. Discrepancies between the observed amount of lensing and the lensing expected based on the visible mass of the near galaxy can be readily interpreted as indicating the presence of dark matter. When the far galaxy, the near galaxy and the

Earth are on a straight line, the bent light forms a circular pattern around the near galaxies, known as an Einstein Ring. A nearly perfect example, discovered in 2007 [7], is shown in Figure 1.2b. The observed size of the Einstein ring is much larger than what would be expected from the visible matter alone.

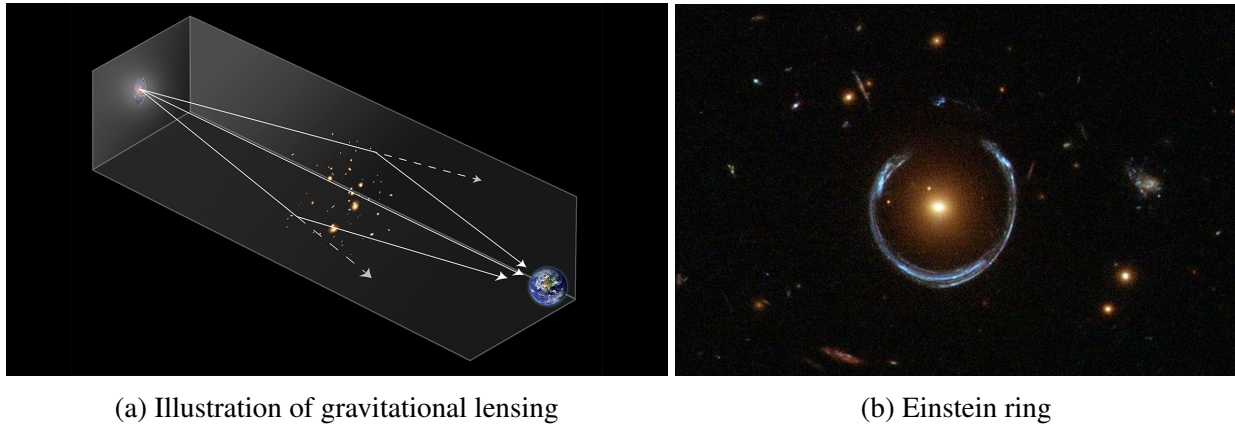


Figure 1.2: This figure shows two images that illustrate how the path of light from a distant object would be observed at the Earth when there is a large amount of mass along the path and how it can be used to provide evidence for dark matter. We show it because the "bending of the path" due to gravitational effects of the mass along the path, known gravitational lensing, can tell us about the amount of mass between the two. Since the amount of lensing is proportional to the amount of mass, comparisons between the observed amount of lensing and the amount of expected lensing from the measured visible mass again provides evidence for dark matter. On the left is a view of the Earth, as well as a near and a far galaxy. The path of the light from the far galaxy is bent as it passes around the near galaxy, giving the illusion that the light from the distant comes from directions not aligned with the near galaxy; the shape of the observed light from the far galaxy tells us about the alignment of the three objects in space and the amount of bending provides a measure of the mass of the near galaxy. On the right is a near perfect example observed by the Hubble Space Telescope, in which the Earth as well as the near and far galaxies are on an almost perfectly straight line, causing the lensed light from the far galaxy to almost completely encircle the near galaxy; the outer circle is referred to as an Einstein ring. The size of the Einstein ring is much larger than that expected from the amount of mass that produces light, indicating both the presence and amount of dark dark matter in the near galaxy. Subfigure (a) is taken from Ref. [8] with image credit by NASA. Subfigure (b) is adapted from Refs. [9] and [10] with image credit by NASA and ESA.

Observations of galaxy clusters that have collided can be interpreted as evidence that dark matter possesses particle-like characteristics. Figure 1.3 shows an image of an in-progress col-

lision between two galaxy clusters, revealing significant discrepancies between the locations of the atomic interactions (from X-ray observations) and the total mass (from gravitational lensing observations) [11]. The X-ray emissions trace the mass distribution of ordinary matter that interacts and slows down during the collision. By contrast, the gravitational lensing map, which traces the total mass distribution, shows that most of the mass has already passed through the collision region with little interaction. This can be explained if the dark matter content of the clusters consist of particles that do not interact electromagnetically, allowing them to pass through largely unaffected.

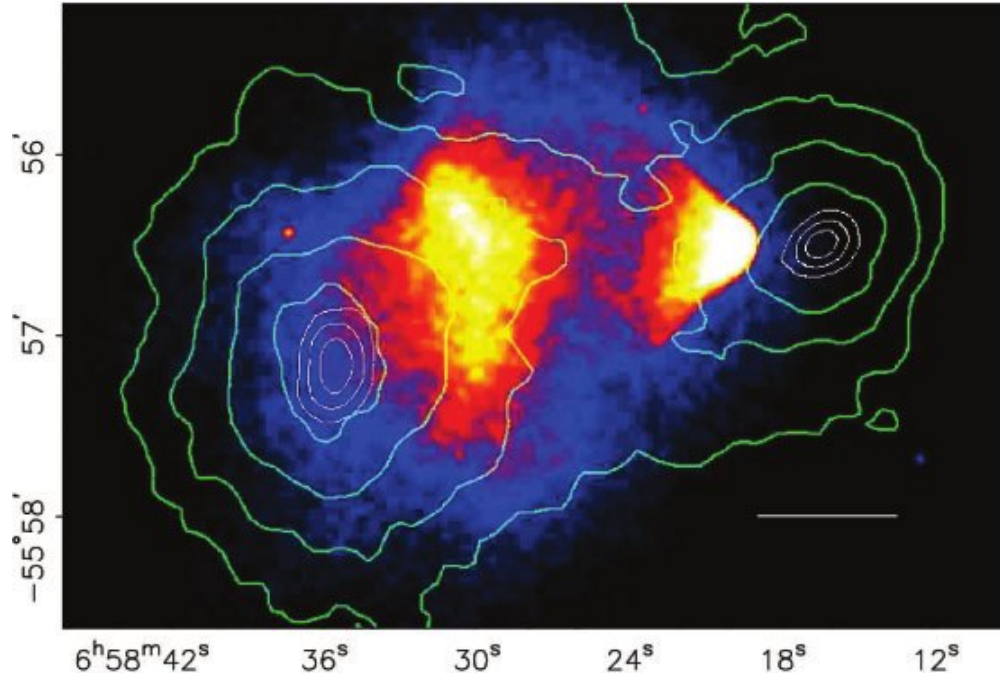


Figure 1.3: This figure shows a superposition of two observations of the mass distributions of two colliding galaxy clusters (known as the bullet cluster). We show it because the mismatched results indicate that the dark matter is both particle-like and that it doesn't interact via the electromagnetic interaction which the normal matter particles do. The heat map with the blue, red and yellow are from the X-ray observations (color means intensity, blue smaller and yellow larger) that are produced from normal matter particles (atoms) colliding with each other, showing the density distributions of the atomic mass. The green contours indicate the amount of mass as estimated using gravitational lensing methods, showing the regions of matter with the highest concentration. Compared to the shape of the X-ray heat map, the concentric contours can be interpreted as the dark matter content of each of the galaxies simply having passed through each other while the atomic collisions slowed down the atomic matter. Figure is taken from Ref. [11].

Having presented evidence supporting the existence of dark matter and its particle-like nature, we next overview a candidate for dark matter particles and the direct detection methods used to potentially observe them.

## **1.2 A Candidate for Dark Matter Particles and Direct Detection Methods**

In this section, we describe a dark matter candidate, Weakly Interacting Massive Particles (WIMPs), and one of the direct detection methods used to search for them. Since the true nature of dark matter remains unclear, and none of the known particles of the standard model of particle physics have the correct properties, scientists have proposed various new particle candidates, each suggesting a detection method, as summarized in Section VII of Ref. [1]. In the first paragraph we describe WIMPs as they provide both a widely studied candidate and detection methods. In the second paragraph we outline a direct detection method to observe rare collisions between WIMPs and atomic nuclei.

The WIMP hypothesis proposes that dark matter consists of electrically neutral particles that interact primarily through gravity and the weak nuclear force. This concept was formally introduced by Steigman and Turner in 1985 [12], based on a combination of astronomical and cosmological considerations, and it aligns with the evidence presented in the previous section, as well as other observations summarized in Ref. [1]. Despite their elusive nature, WIMPs' small but non-vanishing interaction rates offer multiple pathways for both direct and indirect detection.

One method to search for WIMPs is direct detection, which aims to measure a collision between a WIMP and a single atomic nucleus in a laboratory setting. As illustrated in Figure 1.4, a WIMP could interact via the weak force with the nucleus of a normal atom and transfer a small amount of energy to it in the process. This energy can cause subsequent physical processes that, with the aid of detector technologies, can be amplified and converted into measurable electronic signals. More details will be described and discussed in Chapter 3.

Having overviewed one of the dark matter candidates, WIMPs, and discussed the possibility of observing their interaction via direct detection methods, we next overview the SuperCDMS experiment, which applies these concepts and techniques to search for evidence of dark matter

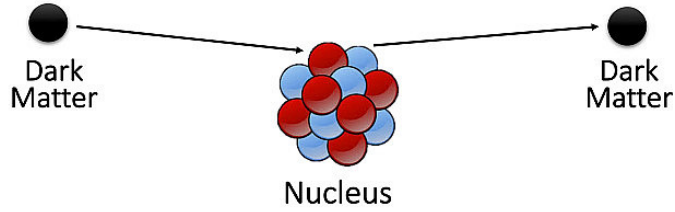


Figure 1.4: This figure shows a diagram of a dark matter particle interacting with a nucleus. We show it because it illustrates the direct detection method used by SuperCDMS experiment. Figure is taken from Ref. [13].

interactions.

### 1.3 Super Cryogenic Dark Matter Search (SuperCDMS) Experiments

In this section, we overview the SuperCDMS experiments, with a focus on one mode targeting low mass WIMPs, CDMSlite. Conceptually, the experiments can be thought of as simple. Since the Earth resides in the Milky Way, which contains dark matter like other galaxies, it is reasonable to expect that a steady stream of dark matter particles will pass through a region in space at any moment in time. By situating a detector expected to be sensitive to dark matter interactions in a location where all other sources of interactions and backgrounds are removed, we have the possibility of a discovery.

In Section 1.3.1 we overview the SuperCDMS experiments at the Soudan Laboratory, outlining the underground facility and the experiment’s physics goals. In Section 1.3.2 we overview the detection principles used in the CDMSlite operating mode. Further information about the SuperCDMS/CDMSlite experiments and the detector will be discussed in Chapters 2 and 3, respectively.

#### 1.3.1 Overview of SuperCDMS at Soudan

In this subsection, we provide an overview of the SuperCDMS experiment at the Soudan Laboratory. As an upgrade to earlier CDMS experiments, SuperCDMS incorporated advanced detector technologies that require cryogenic temperatures ( $\sim$ mK) and was operated between 2011

and 2015 [14]. The deep underground laboratory provided a low-background environment well-suited for dark matter searches, with substantial overburden shielding the detectors in the experiment from cosmic rays. For reasons that will be described in more detail later, the experiments ran in multiple modes using semiconductor detectors equipped with superconducting sensors, with each mode designed to target specific dark matter detection goals. In the first paragraph, we overview the Soudan Laboratory. In the second paragraph, we overview the experiment apparatus that houses the detectors. In the third paragraph, we overview the SuperCDMS data taking modes, with a focus on the CDMSlite mode used in this work.

The Soudan Laboratory sits in a former mine located in Soudan, Minnesota, 2,341 ft (714 m) below the Earth's surface [15]. At this depth, the overlying rock significantly shields the lab from cosmic rays, reducing their intensity by a factor of over 100,000 compared to the surface [16], while dark matter particles are largely unaffected due to their extremely weak interactions.

The experiment includes 15 germanium (Ge) detectors which are sensitive to low-energy interactions and can measure the amount of energy deposited [17]. The apparatus that surrounds them provides the necessary operation environment for the detectors and additional shielding from environmental backgrounds, maintains the detectors operating temperature of approximately several tens of mK, and houses the necessary piping and components for electronic signal readout. More detail will be described in Section 2.1.

Since there are many dark matter candidates beyond the WIMP model, the SuperCDMS experiments utilize multiple data-taking modes and analysis strategies to enable the dark matter search with a wide range of mass (from eV to TeV) as shown in Figure 1.5. This work focuses on the CDMSlite mode, which targets dark matter with masses between 0.3 and 10 GeV and will be overviewed in the next subsection.

With the overview of SuperCDMS at Soudan complete, we next move to provide more details about the CDMSlite mode, which is the focus of this work.



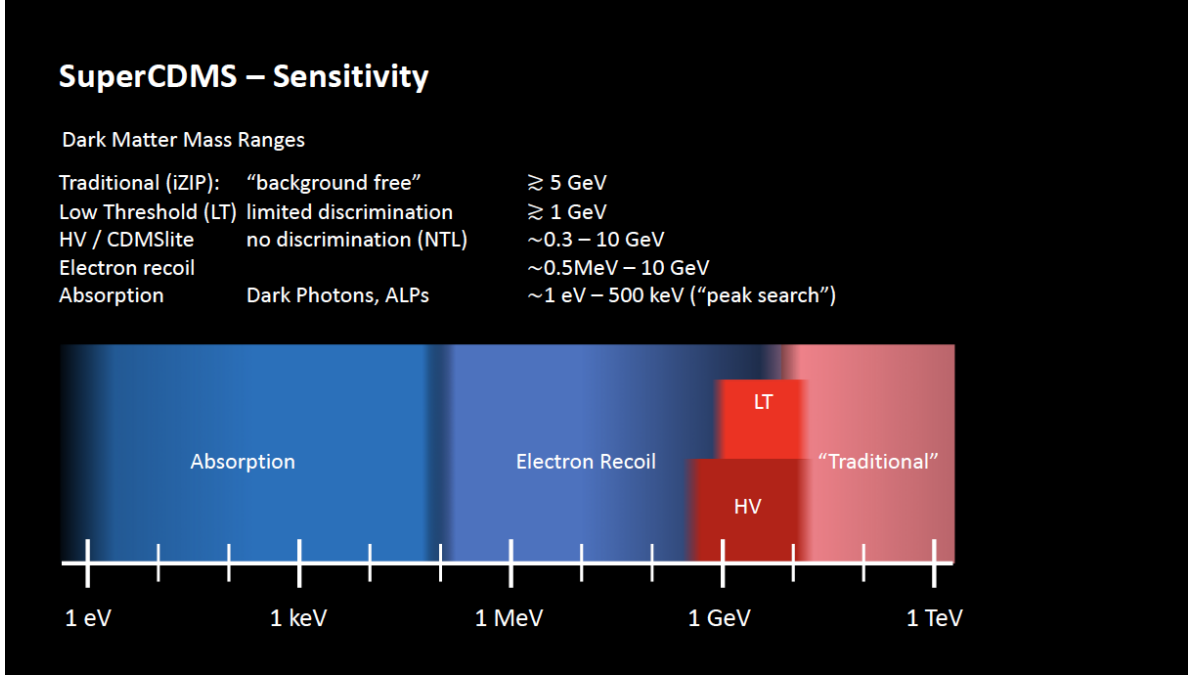


Figure 1.5: This figure shows the different types of mode/analyses done by the SuperCDMS experiments and the potential dark matter masses each would be sensitive to. We show it to illustrate how the CDMSlite mode (this work), referred to as HV in the figure, fits into the big picture of the physics goals for SuperCDMS. It is designed to search for dark matter candidates with masses from 0.3 to 10 GeV. Figure courtesy of the SuperCDMS Collaboration.

### 1.3.2 Overview of the SuperCDMS Low Ionization Threshold Experiment (CDMSlite)

In this subsection, we overview the CDMSlite mode of the SuperCDMS experiments, which aims to detect interactions from WIMPs with masses of 0.3 - 10 GeV, predicted to deposit energies well below  $<10 \text{ keV}$  [14]. At these energies it is very difficult to distinguish between these deposits and electronics noise in the detector. Since noise is omnipresent, the detector must be readout at only specific times, and the decision was made to only read out the detector if there was evidence of a deposit of energy above a certain amount, known as an energy threshold. In principle the lower the threshold where we have still have a good signal-to-noise ratio the more sensitivity to low mass dark matter. For reasons discussed in more detail in Section 3.2.1, a single detector operated at a high bias voltage ( $\sim 70 \text{ V}$ ) collected data, effectively providing a low energy threshold, which is what gives the CDMSlite detector its name. In the first paragraph, we overview the semiconductor

crystal and superconducting sensors of the CDMSlite detector, along with how it converts dark matter interactions into electrical signals. In the second paragraph, we overview how applying a high voltage across the CDMSlite detector gives it sensitivity to small energy deposits. In the third paragraph, we describe the primary method of calibrating the detector response which involves activating Ge nuclei in the detector which later decay and deposit well-known energies.

The CDMSlite detector, like other detectors used in SuperCDMS experiments, is formed from a single Ge crystal with superconducting sensors attached to its surfaces. When a dark matter particle interacts with the Ge crystal, the energy deposit can both liberate electrons from the atoms, leaving vacancies in the atoms which acts like positive charges known as holes, and cause the lattice itself to vibrate, as illustrated in Figure 1.6. The former process is referred to as the creation of electron-hole pairs (also referred to as charges or charge carriers). In the latter process, the lattice vibrations that can propagate throughout the crystal can be described as particles known as phonons. The superconducting sensors absorb the phonons and convert their energy into measurable electrical signals, as outlined in Figure 1.7. More details on these processes will be discussed in Section 3.1.

The CDMSlite detector achieves sensitivity to energy deposits as low as 70 eV [18] by applying a high voltage across the detector. This approach amplifies the production of phonons as charges continuously pick up energy from the electric field and scatter off atoms in the Ge crystal lattice causing it to vibrate, as illustrated in Figure 1.6. The number and energies of the phonons generated is proportional to the applied voltage; thus, at a high voltage, even with a small amount of energy deposit the detector yields enough phonons for the phonon sensors to produce measurable signals. Said differently, they produce a signal above the threshold. Further details are provided in Sections 3.2 and 3.3.

While germanium atoms in the crystal are typically stable, a Ge-70 nucleus can be converted into an unstable Ge-71 nucleus upon neutron capture and its decay products can be used to calibrate the detectors response to energy deposits. Germanium has five naturally occurring isotopes (Ge-70, Ge-72, Ge-73, Ge-74, and Ge-76) [19], of which Ge-70 have a natural abundance of 20.5%. A large sample of Ge-71 decay events can be generated by placing an external neutron source, such as

Cf-252, near the detector. Following the activation, data taking is initiated as Ge-71 atoms start to decay. Each one releases one of three energies between 0.1 to 10 keV, which well aligns with the CDMSlite target energy range of 70 eV to 10 keV. More details are described in Section 2.2.

With our overviews of the SuperCDMS experiment and CDMSlite mode complete, we next outline the rest of the thesis.

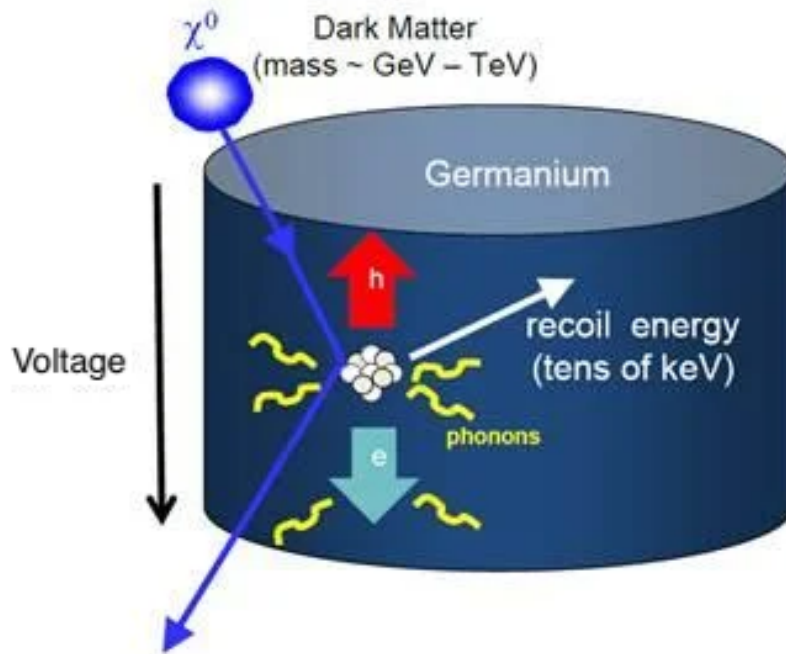


Figure 1.6: This figure shows a cartoon of a dark matter particle scattering off an atom in a single-crystal germanium detector, depositing energy which subsequently produces particles which can be readily detected. We show it to illustrate the physics picture of what happens inside the detector in the SuperCDMS low ionization threshold experiment (CDMSlite) for use in searches. When a dark matter particle (notated as  $\chi^0$  in this figure) travels through the detector and interacts, the target particle in the detector gains energy (referred as recoil energy). This process ionizes electrons from the atoms, leaving vacancies in the atoms which acts like positive charges known as holes, and causes lattice vibrations known as phonons (squiggly yellow lines). Any electrons and holes (blue and red arrows, both referred to as charges or charge carriers) get accelerated by the electric field, and bounce into the lattice which produces more phonons. This process, called the NTL effect which will be described in detail in Section 3.2.1, significantly amplifies the signal from the recoil energy from the dark matter particle. Figure courtesy of the SuperCDMS Collaboration.

## CDMSlite Detector's Response and Signal Readout

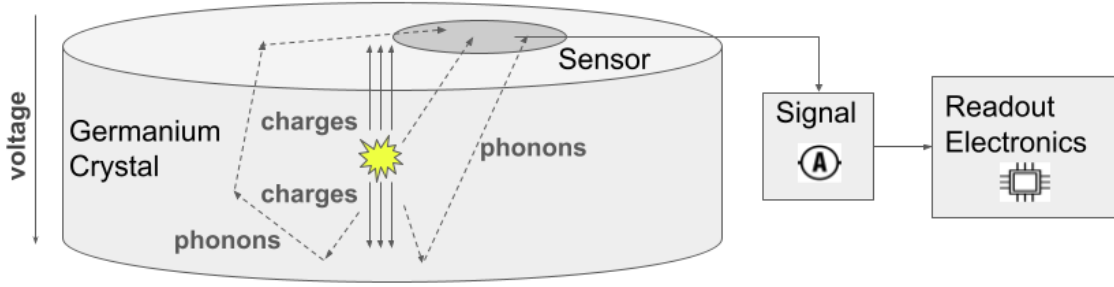


Figure 1.7: This figure shows a simplified diagram of the CDMSlite detector and its signal readout system, along with an interaction occurring inside the detector. We show it to illustrate the set of processes that occur within the detector from the initial interaction all the way to the readout by the electronics. When an interaction occurs inside the detector (yellow), it produces both charge carriers and phonons. The charges are accelerated to the detector surfaces by a voltage, while the phonons created in the transport process propagate through the crystal and are eventually absorbed by sensors; only a single sensor is shown here for simplicity. These sensors, integrated into readout circuits shown on the right, generate current signals upon phonon absorption. These physics processes will be described in detail in Chapter 3 and the simulation of them will be described in Chapter 5.

### 1.4 Outline of this Thesis

In this section, we describe the goals of this work and outline the contents of each chapter in the rest of this thesis. Our primary goal is to deepen our understanding of the CDMSlite detector's response via simulation and comparison to real experimental data to assist in dark matter searches. While, in principle, the work with the CDMSlite experiment could lead to a discovery of dark matter in the data, or at least produce the world's most sensitive search, previous analyses of the collected data found no evidence for dark matter interactions [14, 18]. On the other hand, those analyses used a number of simplifying assumptions about the detector response to energy deposits, which perhaps limited both the sensitivity and robustness of their results. Since improvements in sensitivity are expected to come from a more detailed understanding of the detector response, we focus there as it can enhance data analysis in the upcoming data run with even more sensitive detectors, as well as the design of future detectors.

In real-world experiments, we can only indirectly infer information about the interaction via the data read out by electronics; there is no mechanism to directly measure the interaction or the subsequent physical processes inside the detector and its sensors. Simulation tools allow us to model these internal microphysical processes, as shown in Figure 1.7, and produce results in the same format as real experimental data. By comparing the similarities and differences between simulated and real data when the original interaction type is known and understood, we can gain insight into what happens during the experiment to more accurately infer information about the original interaction, as well as identify areas where our understanding or modeling may be incomplete.

The first set of chapters are about the detector, the data and the simulations. In Chapter 2, we describe the relevant details about the SuperCDMS/CDMSlite experiment, including the apparatus and detector, the methods of producing known energies to calibrate the detector's response, the procedure of data taking, as well as the main types of event sources. In Chapter 3, we discuss the microphysical interactions and processes underlying the detection, focusing on the interactions inside the detector that effectively convert the energy deposit to lattice vibration (phonons), and ultimately produce electronic signals for energy measurement and further analysis. In Chapter 4, we describe the interpretation of pulse shapes, the selection of events during stable data taking and the rejection of background events, and the identification of 10 keV energy deposit events from the calibration source for analysis. In Chapter 5, we describe the SuperCDMS simulation infrastructure, the physical processes simulated, along with the samples created for this work.

The second set of chapters focus on comparisons of simulated results to expectations and real data, what we can learn, and conclusions. In Chapter 6, we compare the collected phonon energy and the shape of pulses produced in simulation to our expectations, including discussion of the locations within the detector where interactions are well and poorly measured, and the similarities and differences observed in the pulse shape comparisons. In Chapter 7, we describe the phonon absorption by the individual sensors as a function of time and position, and model the phonon energy collection with early and later components. In Chapter 8, we highlight the potential advantages of using simulations by using the predictions from the simulation in the development of methods for

rejecting poorly-measured events and estimating the interaction positions of well-measured events. In Chapter 9, we present our study of the later portion of pulses (pulse tails) in both simulated and real data, including a channel-by-channel relative calibration of the pulses from the four phonon channels of the CDMSlite detector to ensure consistent scaling between simulation and real data for comparison. In Chapter 10, we compare the simulated pulses to the real experimental pulses after the relative calibration, and propose several hypotheses to potentially explain the observed differences. In the final chapter, Chapter 11, we summarize the results and describe plans for future work based on our analysis results and conclude.

With our introduction of this thesis complete, we move forward to describe the experiment in the next chapter.

## 2. EXPERIMENT DESCRIPTION: SUPERCDMS EXPERIMENT AND CDMSLITE DETECTOR

In the previous chapter we summarized the motivation and goals for this work and overviewed the SuperCDMS experiments and the CDMSlite detector. In this chapter and the next (Chapters 2 and 3), we provide more detail about how the detector provides sensitivity to dark matter interactions, as viewed from the different vantage points shown in Figures 1.5 - 1.7. For pedagogical reasons we will start with the pieces that are well-understood, including the experimental apparatus that surrounds the detector, the methods of producing known energy deposits in the detector, and the methods of reading out the detector signals. After that, we work our way inwards to focus on the physical processes that occur within the detectors as those are the least understood and where we want to focus. Specifically, in Chapter 2, we focus on the SuperCDMS apparatus and the CDMSlite detector, as shown in Figures 2.1 and 2.2, as well as the data taking procedure. In Chapter 3 we discuss the detector physics utilized to convert interactions within the detector into pulses for readout and analysis, as shown in Figure 1.7.

To set the stage for describing the detector response and the subsequent discussion of the simulations and data analysis, this chapter focuses on the multiple aspects of the experiment for this work. It includes the main components of the experimental apparatus and detector, the methods used to produce known energy deposits for calibrating the detector's response, an overview of the detector signal readout and processing procedures, and the expectations for the data. In Section 2.1, we overview the SuperCDMS apparatus used at the Soudan Laboratory, and the CDMSlite detector along with its voltage configuration. In Section 2.2, we discuss the set of processes that result in known energy deposits produced inside the detector for use in calibrating the detector's response; this includes the choice of source, its underlying physics, and the experimental setup. In Section 2.3, we describe how the detector signals are read out, processed and recorded by the data acquisition (DAQ) system. In Section 2.4, we outline the expectations for the data, specifying the types of events from various sources, which sets the stage for the discussion of the physical response processes

inside the detector in Chapter 3.

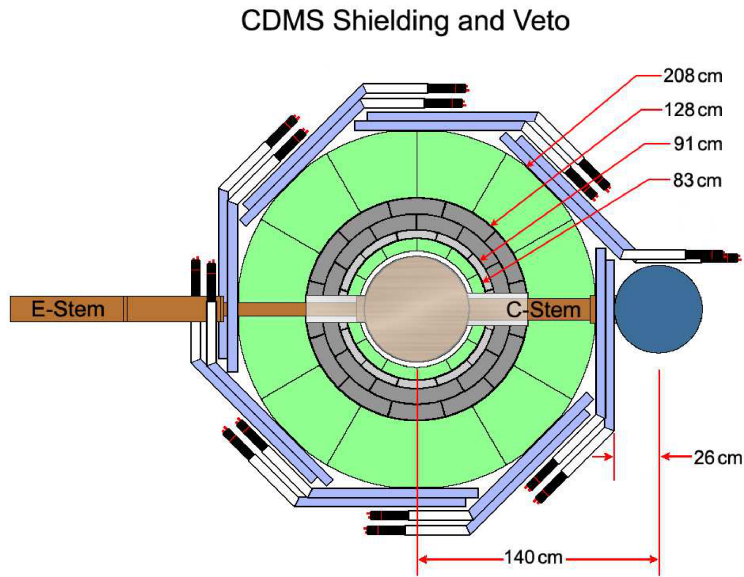
## **2.1 The SuperCDMS Experimental Apparatus and the CDMSlite Detector**

In this section, we overview the SuperCDMS apparatus used at the Soudan Underground Laboratory, and the CDMSlite detector, as shown in Figures 2.1 and 2.2. In the first paragraph, we describe the main parts of the SuperCDMS apparatus, along with their functions. In the second paragraph, we describe the hardware components of the detector, including the germanium crystal, the electrodes and the superconducting sensors. In the third paragraph, we describe the voltage configuration of the detector, along with the resulting electric field. Some additional details for interested readers are presented in Appendix A.

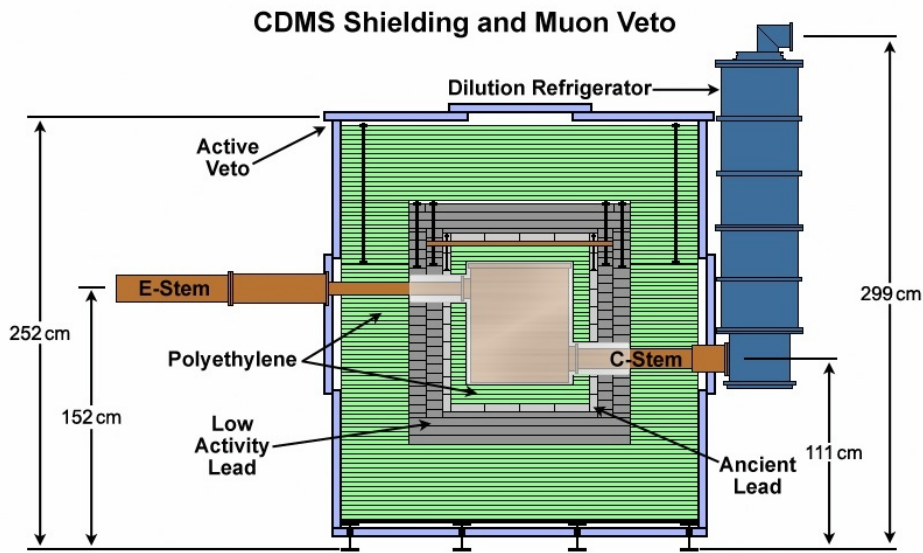
The SuperCDMS apparatus, as shown in Figure 2.1, has a number of important components, including the cryogenic chamber for placing detectors, shielding, a refrigerator that provides the low-temperature environment, and two sets of pipes that connect them to the outside world. The chamber for placing detectors, including the CDMSlite detector, is located at the center of the apparatus. Surrounding the chamber are multiple layers of shielding to reduce backgrounds of various kinds: polyethylene for slowing down neutrons, low-activity lead for blocking photons, and overlapping veto panels used for identifying external events that are not blocked by the overburden. Two pipes are connected to the chamber via shielding plugs on opposite sides. The ‘E-stem’ (Electronics) pipe provides connections between the detectors and the readout electronics and the ‘C-stem’ (Cryogenic) connects the chamber enclosing the detectors to the rest of the refrigeration system that keeps the operation temperature in the milliKelvin regime. These two pipes also provide some shielding function and allow calibration sources to be placed closer to the detectors, past some of the shielding. For a more detailed description, see Chapter 4 of Ref. [20].

The CDMSlite detector consists of several components, including a germanium crystal, a set of electrodes (which also function as charge sensors) and superconducting phonon sensor pads as well as a set of readout pins, all of which is surrounded by a copper housing. The germanium component is a single crystal which is roughly cylindrical, with a diameter of  $\sim 75$  mm, a height of  $\sim 25$  mm, and a mass of  $\sim 600$  g. The electrodes for voltage biasing and the superconducting phonon sensors





(a) SuperCDMS apparatus at the Soudan Laboratory (top view)



(b) SuperCDMS apparatus at the Soudan Laboratory (side view)

Figure 2.1: This figure shows two views of the SuperCDMS apparatus used at the Soudan Laboratory. We show it to illustrate the main components which both shield the detectors at the center and keep them at a controlled temperature. Polyethylene (shown in green) is used to reduce the number of neutrons which enter the detectors. Similarly, the ancient lead (shown in grey) is used to block photons. The overlapping panels (blue&white&black) visible in the image at the top, referred to as the muon veto system, allow us to identify muon particles that are not blocked by the overburden. Two pipes are connected to the chamber via shielding plugs on opposite sides, the ‘E-stem’ pipe providing connections to electronics and the ‘C-stem’ pipe to the cryogenics that keeps temperatures at about tens of milliKelvin. Calibration sources can be placed in the pipes closer to the detector, inside the shielding. Figure courtesy of the SuperCDMS Collaboration.

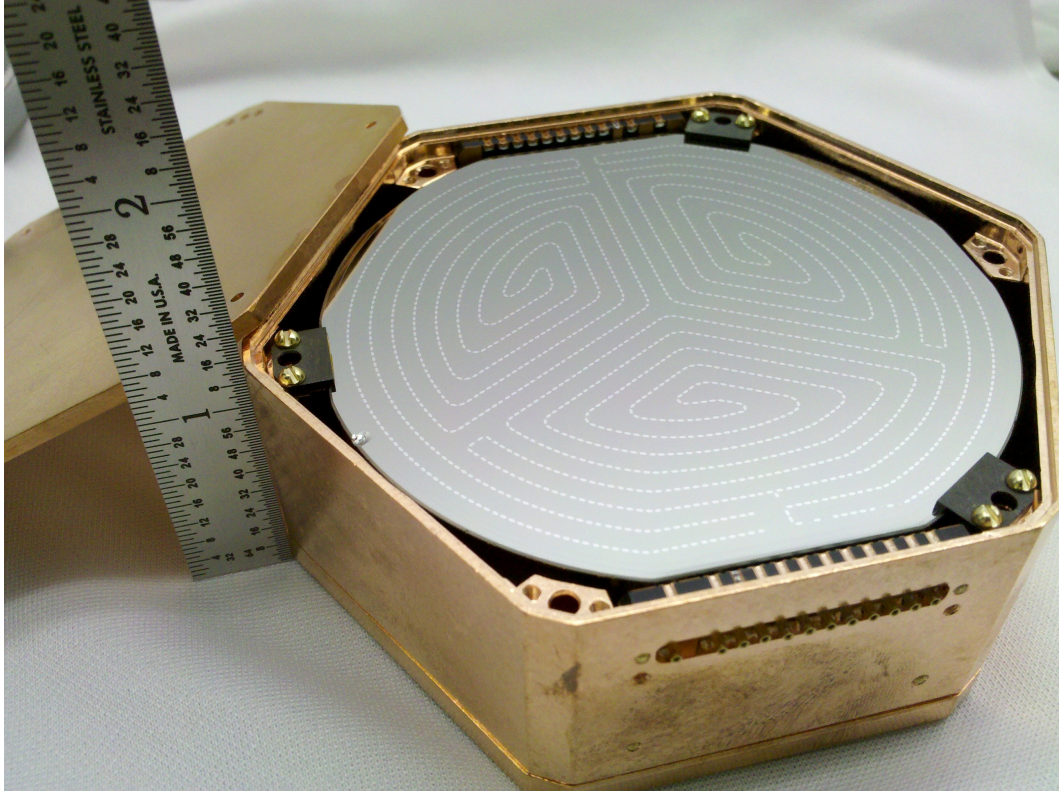


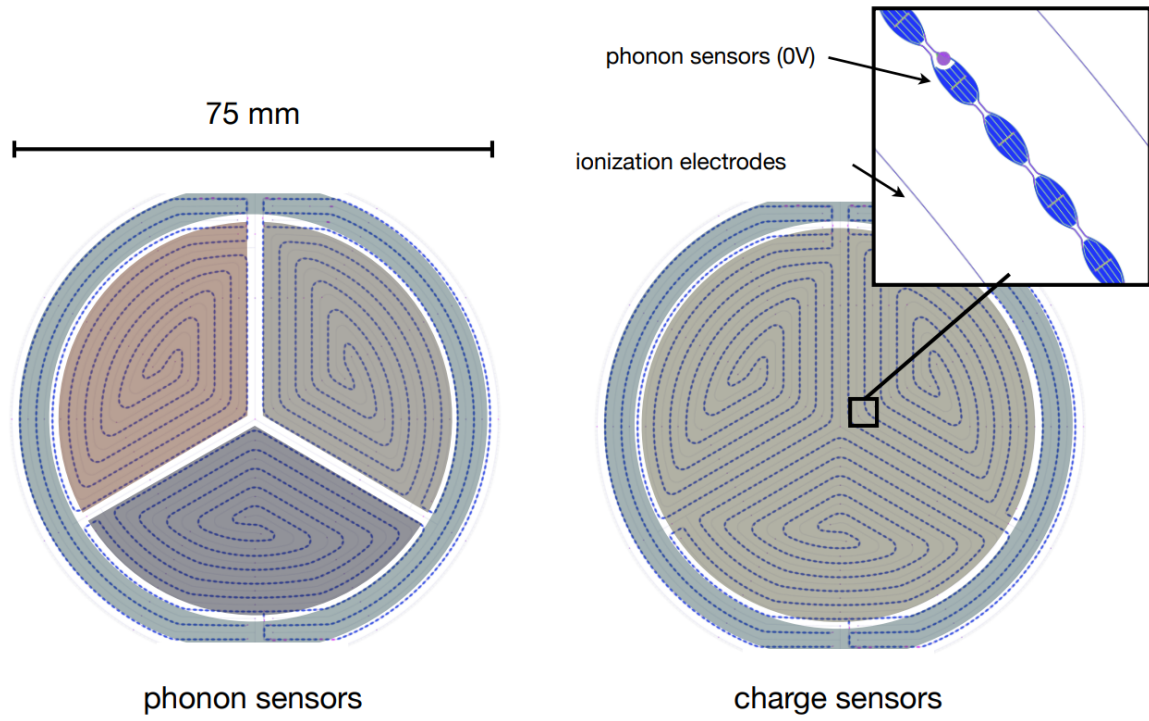
Figure 2.2: This figure shows a photograph of the CDMSlite detector from the top view. We show it to indicate its size and shape, the locations of sensors (white lines), the copper housing and the non-circular regions, known as ‘flats,’ and where the readout cables are attached. A more detailed description of the geometry is given in Figure A.2. The lines on the surface contain the electrodes and charge sensors (some electrodes are used for sensing charge signals), interspersed with the superconducting sensors (also referred to as phonon sensors) that are grouped into channels as shown in Figure 2.3. The whole detector is contained inside a copper frame. Figure courtesy of the SuperCDMS Collaboration.

for energy measurement are attached to the top and bottom surfaces of the germanium crystal as shown in Figure 2.3. The electrodes are partitioned into an inner disk and an outer ring, while the superconducting sensors are organized into three inner channels and one outer channel. The surface electronics are connected to multiple pins that provide interfacing and signal readout<sup>1</sup> and the copper housing is six-sided and connected to ground.

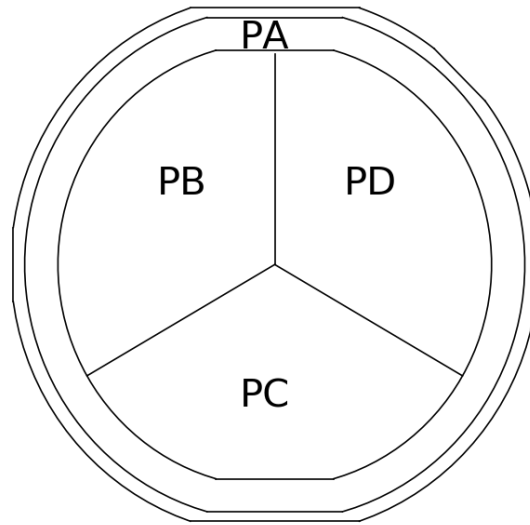
A bias voltage of 70 V is applied across the CDMSlite detector, and a mostly-uniform electric field is generated as shown in Figure 2.4. The top electrodes are connected to 0 V, while the bottom

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<sup>1</sup>More details in Appendix A.



(a) Configuration of sensors and electrodes of CDMSlite detector



(b) Phonon channel map of CDMSlite detector

Figure 2.3: This figure shows a more detailed layout of the superconducting phonon sensors and the electrodes (which also function as charge sensors) that are attached on the top and bottom surfaces of the CDMSlite detector, as shown in Figure 2.2. We show it to indicate the locations of the individual sensors and electrodes. The phonon sensors are grouped into four channels, labeled as PA, PB, PC and PD, respectively. We note that in the CDMSlite mode only the top side of the detector is read out. The figures on the top are taken from Ref. [20].

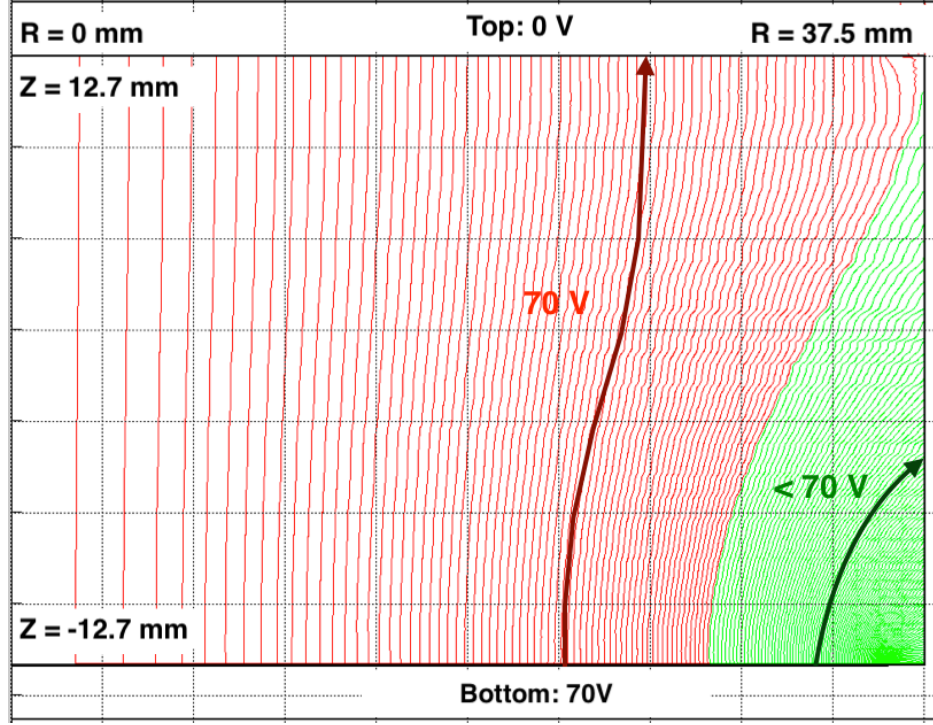


Figure 2.4: This figure shows the electric field map inside the CDMSlite detector in the RZ plane. We show it because the voltage determines both the path of any charge as well as how much energy it will pick up along the way. The full voltage drop is 70 V in most regions (red lines), but is reduced to  $< 70$  V in the triangle-like region (green lines) near the sidewall due to the grounded housing (0 V). When an interaction occurs in the green regions, we will not get a full measurement of energy. Figure is adapted from the SuperCDMS Collaboration.

electrodes are biased at +70 V. Of particular note is that the copper housing, as shown in Figure 2.2, affects the electric field at large radius. The triangle-like region in the RZ plane near the sidewall experiences a reduced voltage bias ( $< 70$  V), which impacts the energy measurement for reasons that will be described in Section 3.2.2.

Having overviewed the SuperCDMS experimental apparatus and the CDMSlite detector, in the next section we describe the processes which produce known energy deposits in the germanium crystal of the detector. These deposits help establish the relationship between the detector output and the interaction energy, a process known as energy calibration. The underlying physical processes of the detector's response will be described in detail in Chapter 3.

## 2.2 Producing Known Energy Deposits for Calibrating the Detector's Response

In this section we describe the procedures by which known energy deposits are caused to occur within the detector to calibrate its response. In general, energy calibration describes quantifying the relationship between known energy deposits within the detector and the detector outputs. In our case, the energy deposits come from the decay of Ge-71 atoms, which has the advantage of producing final state energies in the range targeted by CDMSlite's dark matter search. The procedure includes multiple steps and requires the infrastructure surrounding the detector. We start our description by noting that the germanium crystal is populated with Ge-70 atoms and that the process of creating a Ge-71 requires an external source of neutrons. Figure 2.5 illustrates a Cf-252 source placed near the detector, which emits a neutron that is subsequently absorbed by a Ge-70 atom to produce a Ge-71 atom. In the first paragraph, we motivate the choice of the calibration source, Ge-71, as its decay provides energy deposits within the range targeted by the CDMSlite experiment and can be readily be produced inside the detector. In the second paragraph, we describe the setup to create multiple Ge-71 atoms within the detector by placing an external Cf-252 source near the detector. In the third paragraph, we describe some specifics about the Ge-71's electron capture decay process that determine the three emitted energies and their associated probabilities.

The calibration source Ge-71 was chosen because its decay provides energy deposits within the range targeted by the CDMSlite experiment and can be produced inside the detector itself. All Ge-71 atoms undergo 100% electron capture decay, and emit three characteristic energies of approximately 10, 1 and 0.1 keV, as discussed in detail below. These energies well-align with the expected energy deposits (from 70 eV to 10 keV) from low-mass dark matter particles ( $< 10$  GeV) that the CDMSlite detector is designed to detect. In addition, Ge-71 can be conveniently generated by introducing neutrons from a neutron-emitting source to interact with Ge-70 nucleus that are naturally present in the detector.

The processes involved in creating Ge-71 atoms which decay within the detector are shown in Figure 2.5 and starts by placing an external Cf-252 source near the detector. A small capsule of Cf-252, a neutron-emitting source, is positioned either in the C-Stem or E-Stem of the apparatus



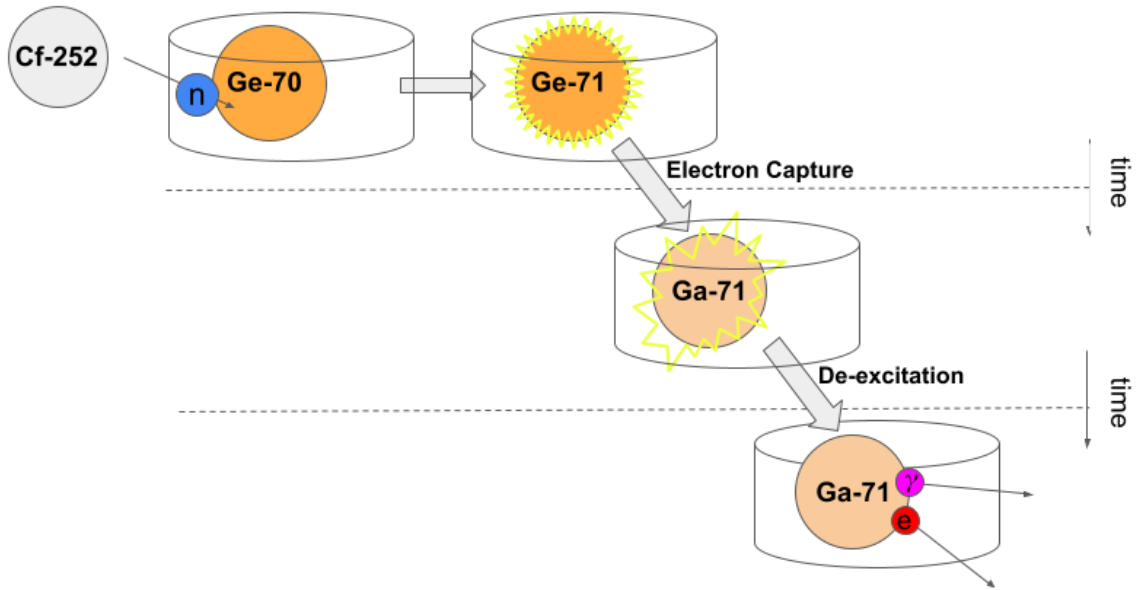
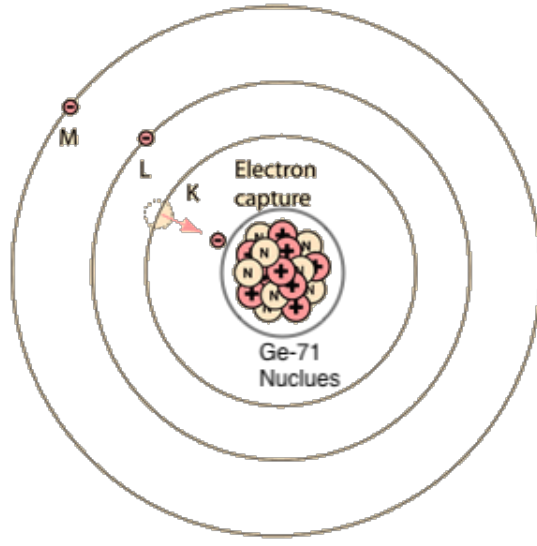
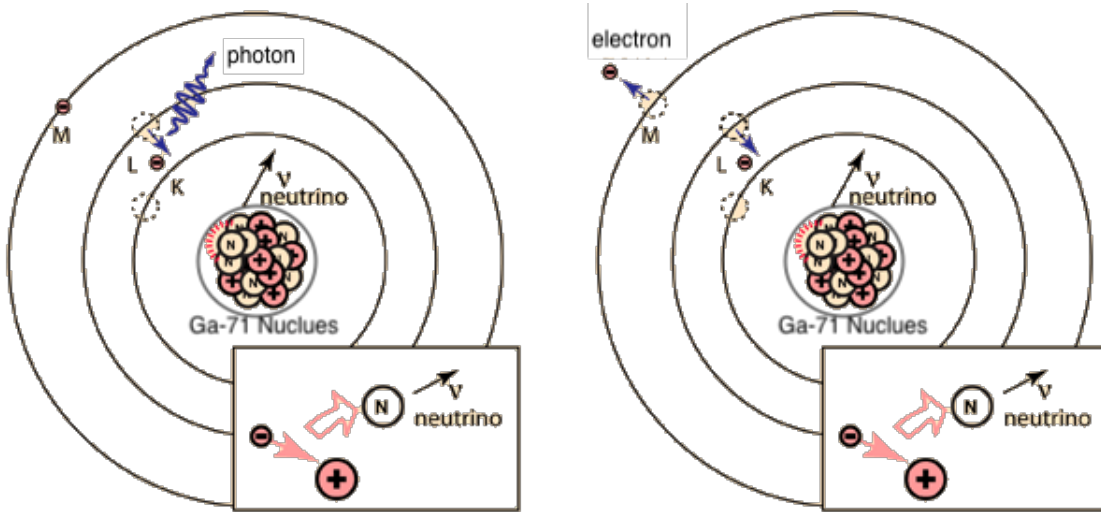


Figure 2.5: This figure shows three diagrams of the stages of a Ge-70 nucleus inside the detector absorbing a neutron emitted from Cf-252, becoming a Ge-71 nucleus and then decaying into a Ga-71 nucleus with the subsequent emission of photons and/or electrons. We show it because the three most common energies ( $\sim 10$  keV,  $\sim 1$  keV,  $\sim 0.1$  keV) released by this physics process are used for energy calibration for the CDMSlite detector. In the top row we see a neutron from a Cf-252 nucleus impinging on a Ge-70 nucleus in the detector, getting captured and becoming unstable Ge-71. From the top to the middle, the Ge-71 atom captures an orbital electron and becomes a Ga-71 atom that is in an excited state. In the bottom, the Ga-71 atom de-excites and emits electrons and/or photons, with the total energy equal to binding energy of the captured orbital electron. More details about this process are given in Figure 2.6.



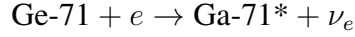
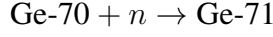
(a) The first stage where a K-shell electron is captured by a Ge-71 nucleus



(b) The second stage where the Ge-71 nucleus transforms into Ga-71 and the atom emits photons (left) and/or electrons (right)

Figure 2.6: This figure shows two sets of diagrams illustrating electron capture by a Ge-71 nucleus and the subsequent de-excitation of the daughter nucleus, Ga-71. We show it to illustrate the two stages of Ge-71 electron capture decay, which can produce three known energies used in energy calibration for the CDMSlite detector. The top diagram shows the first stage where the nucleus of a Ge-71 atom captures an electron (in this example from the K-shell) and then becomes an excited Ga-71 atom. The bottom diagram shows the two components of the second stage where the Ga-71 atom quickly de-excites: electrons in higher shells fill the vacant spots along with emitting photons (on the left) and/or ejecting electron in outer shells (on the right). This multi-step process shifts the vacant spot to the outer shells until a stable electron configuration is reached. More information on the full list of high probability processes are listed in Table 2.1. Figures are adapted from Ref. [21].

shown in Figure 2.1. A fraction of the neutrons emitted travel to the detector and activate the Ge-70 atoms into Ge-71. It is just a matter of time (the half-life is about 11.43 days [22]) before the Ge-71 nucleus captures one of its orbital electrons, transforming into Ga-71 and then emitting electrons and photons that deposit energies within the detector. The full sequence is



where the \* indicates an excited state and the labels refer to the nucleus of the atoms only.

The Ge-71 atoms decay via electron capture, in which the nucleus absorbs one of its orbital electrons, primarily from the K or L shells, transforms into a different nucleus, and emits photons and electrons. The example in Figure 2.6 shows a Ge-71 nucleus capturing an electron from the K-shell to become a Ga-71 in an excited state. An electron from a higher shell subsequently fills the vacancy, emitting photons and/or ejecting electrons in other shells. Each of these emitted particles can be fully absorbed within the detector and produce measurable energy deposits. Since a Ge-71 nucleus can capture an electron from the K, L, or M shell, the energies released correspond to the binding energies of the captured electrons which are 10.367, 1.299, and 0.160 keV, with probabilities of 87.59%, 10.49%, and 1.92%, respectively, as listed in Table 2.1 [23, 24].

Table 2.1: This table lists the probabilities of orbital electron capture by the nucleus of a Ge-71 atom and the electron binding energies of the resulting Ga-71 atom. We include it because the three energies are used to calibrate the CDMSlite detector. Data source: probability of electron capture (Ge-71) is from Ref. [23]; binding energy (Ga-71) is from Ref. [24].

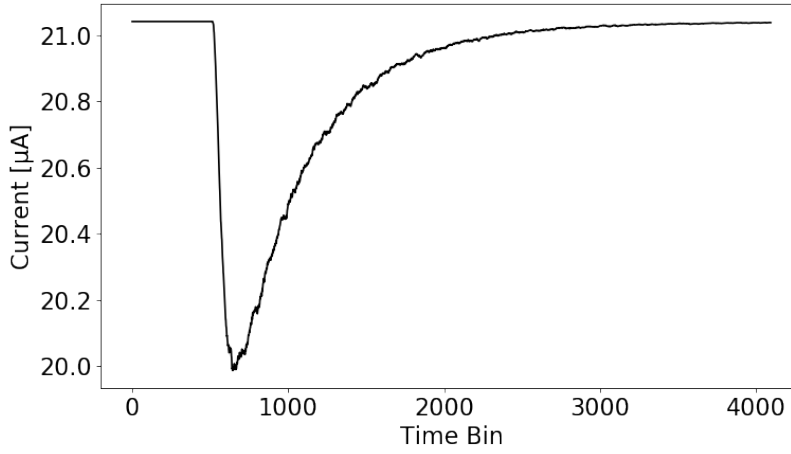
| Shell | Probability of Electron Capture (Ge-71) | Binding Energy (Ga-71) [keV] |
|-------|-----------------------------------------|------------------------------|
| K     | 87.59%                                  | 10.367                       |
| L     | 10.49%                                  | 1.299                        |
| M     | 1.92%                                   | 0.160                        |
| N     | neglected                               | no data                      |



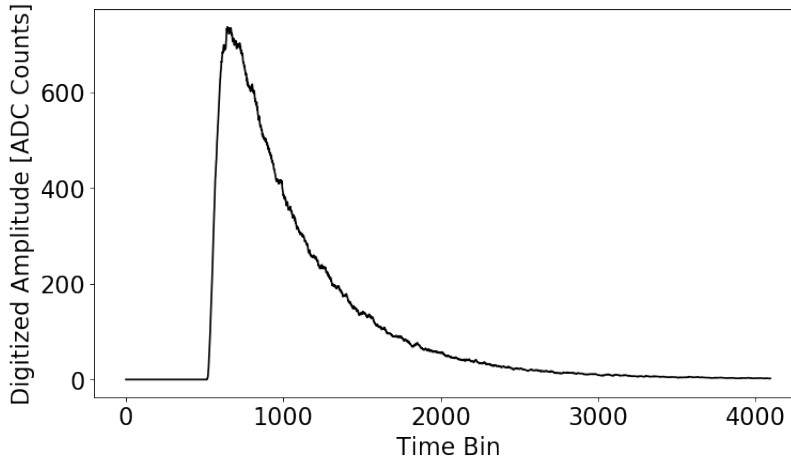
Having motivated the choice of Ge-71 for calibrating the response from the CDMSlite detector, and described the procedure for its production and the microphysics of its electron capture decay, we next move to describe the other end of the experimental process: signal readout, processing, and storage of data as shown on the right-hand side of Figure 1.7. Note that we will come back to the physical processes within the detector that convert the energy deposits into signals in the next chapter.

### **2.3 Detector Signal Readout, Processing and Event Recording**

For the reasons described above we will defer the discussion of the processes that occur inside the crystal and superconductors until Chapter 3, and focus here on the processes after the sensor creation of signals. In this section we summarize the processes shown on the right-hand side of Figure 1.7 which include how signals from the CDMSlite detector are read out, processed, and ultimately recorded as digitized pulses, all of which come after the processes shown in Figure 1.6. This portion of the process starts with the phonon sensors shown in Figure 2.3 and is managed by the readout electronics and the Data Acquisition (DAQ) systems, which are described in detail in Refs. [25, 26]. When an interaction occurs inside the detector, a series of processes leads to the collection of energy and production of a current signal with a shape like that shown in Figure 2.7a. It is then processed through the readout electronics and the DAQ, undergoing steps such as electronic signal amplification, event selection (also known as triggering), and digitization. The signal is ultimately recorded as a pulse like that shown in Figure 2.7b. From these recorded pulses, physical quantities can be determined for analysis as will be described in Section 4.1. We note that the readout electronics introduce noise, and errors can occur during event recording which requires examination of both the pulse shapes and associated experimental parameters to identify and reject problematic events, as discussed in next section. In the first paragraph, we describe how the current signal from a channel is readout and processed by the readout electronics, and ultimately recorded as digitized pulse shapes by the DAQ system. In the second paragraph, we describe how the combination of pulses, together with the associated experiment parameters, are recorded as individual events that form the basis for the data analysis presented in later sections and chapters.



(a) A simulated example current signal directly out of the phonon sensors of the CDMSlite detector



(b) A simulated example pulse out of detector readout from the SuperCDMS Data Acquisition (DAQ) system

Figure 2.7: This figure shows two different simulated versions of the output as a function of time (known as a signal or pulse) for the same example event out of two different stages: directly out of the phonon sensors of the CDMSlite detector and directly out of the Data Acquisition (DAQ) system. While the simulation details will not be discussed until Chapter 6, we use their results to illustrate the input and output of the DAQ. The top is a simulation of the current signal out of the detector in  $\mu\text{A}$ , where the results are integrated into total of 4096 bins with a bin width of  $1.6 \mu\text{s}$ . The bottom is the same pulse but after processing by the DAQ which amplifies, flips the pulse and digitizes it with the same bin numbers and bin width; the output is in Analog-to-Digital Converter (ADC) units which we will refer to as ADC Counts.

The current signal for a single channels worth of superconducting sensors is read out and processed by the readout electronics, and ultimately recorded in digitized form by the DAQ. The electronics consist of two layers: cold electronics that are installed within the experimental apparatus and warm electronics that are located externally and operated at room temperature. The cold electronics perform the initial amplification directly out of the sensors and transmit the signals out of the apparatus through the E-stem as shown in Figure 2.1. The signals are then processed by the warm electronics in three steps. The first is additional amplification, signal conditioning, and filtering to improve the signal-to-noise ratio. The second step is to decide whether to write out the information from the sensor to disk, known as triggering. If the summed signal from the four channels exceeds a predefined threshold, the electronics deem it worthy of potential future study as a candidate for being a particle interaction. The sensor output both before and after the shape shown in Figure 2.7 are recorded, and is referred to as an event. Each event that passes the trigger requirements enters the third stage where the pulse is digitized with the results recorded in ADC (Analog-to-Digital Converter) counts after integration into a total of 4096 bins with a bin width of  $1.6 \mu\text{s}$  and then readout by the DAQ system.

The combination of pulses, together with the associated experiment parameters, are recorded as individual events that form the basis for the data analysis presented in later sections and chapters. Each of the four channels shown in Figure 2.3b produces its own digitized pulse, like the one shown in Figure 2.7b. Of note is that the readout is designed such that the current output from each channel is recorded for a fixed amount of time before the interaction, and the full readout time is long enough to record the current after any pulse from an interaction is expected to end. The portion of the pulse shape before the event provides information about the noise levels at the time of the interaction. When there is an interaction the current shape has fast-rising and then slow-falling components. Additionally, other information about the event is recorded such as the time of triggering, voltage, and cryostat temperature. It is also worth noting that, for illustration purposes, Figure 2.7b shows the combination of the pulses used in the triggering decision, while the pulse shape from an individual channel can differ significantly. By interpreting or directly analyzing these pulses individually or in

combination, we can estimate the energy and position of the interaction as well as determine other things about the event as will be discussed in Chapters 4 and 8 - 10.

Having described how the detector signals are read out, processed through multiple stages of electronics, and ultimately recorded by the DAQ system, we now turn to overview the dominant sources expected to produce events in the data, including those erroneously introduced by the DAQ system.

## **2.4 Classifying Event Sources: An Overview of the Data Expectations**

In this section, we discuss the various sources of events we expect to have in the data.<sup>2</sup> While the CDMSlite detector is designed to record both calibration events and WIMP interactions, we expect some number of events from external photons, neutrinos, and muons. In addition we expect events to be recorded due to experimental operation issues, for example, when the detector or apparatus was not functioning properly, or when noise in the system fluctuates in such a way that the trigger fires and the current in the channels are read out. A related issue is when an event from one of the sources has some form of measurement problem, giving the appearance of being from an unrelated source. We will need to use various processes to remove events from unwanted or unexpected sources, but do so in a way that retains events that are likely to be useful. Below we summarize the event sources and factors that impact the distributions of the events, while the methods to separate these sources are discussed later in Section 4.2. In the first paragraph we describe the set of events from Ge-71 with their three characteristic energies. In the second paragraph, we describe other event sources including photons, neutrinos from external experiments, and cosmic-ray muons, which will need to be rejected. In the third paragraph, we describe the ways in which data taking and event recording can be affected by abnormal-but-transient experimental conditions, such as deviations in temperature or the voltage across the detector being different from its intended value, which need to be rejected. In the fourth paragraph, we describe events mistakenly recorded due to electronic errors or noise, which will also need to be rejected.

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<sup>2</sup>Data-taking in the CDMSlite mode covers three run periods [14, 18]. Run 1 was the test run. Run 2 used a voltage of 70 V and the data is used for this work. Run 3 was similar to Run 2 but with a voltage of 75 V.

One of the main sources of events is from Ge-71. Each event will deposit one of the three characteristic energies into the CDMSlite detector through the emission of electrons and photons, as described in Section 2.2. The energy-related quantities are derived by interpreting the pulse signals, as will be detailed in Section 4.1. As we will see in Chapter 4, the energy spectrum exhibits three peaks corresponding to the energies emitted by Ge-71 as listed in Table 2.1.

Other event sources include photons and neutrons from the cavern, neutrinos from external experiments, and cosmic-ray muons. Photons and neutrons that make it through the shielding can deposit energy across a wide range, but we currently have no reliable way to distinguish them from signal events. Some neutrinos originate from the NuMI (Neutrinos at the Main Injector) beam at Fermilab [27], and can be identified by correlating event data-recording time with known beam times. Neutrinos from cosmic sources are expected to be negligible due to their low interaction cross section. Muons from cosmic rays that take a path that traverses the detectors can be identified and removed using their ionizing interactions in the veto planes surrounding the apparatus, as illustrated in Figure 2.1.

Electronics noise or errors can also be mistakenly recorded as an event by the trigger. Noise fluctuations, especially under low threshold settings in CDMSlite, can mimic an energy deposit and lead to the recording of spurious events. Similarly, a malfunction in the electronics can falsely trigger the system, resulting in the readout of the detectors even when no actual interaction or energy deposit occurred in the detector. Sophisticated methods, after data taking, can be used to reject most of these events by comparing the readout pulse shapes to expectations, as described in Section 4.1.

Abnormal experimental conditions, such as deviations from the baseline temperature or voltage, can cause events from the sources above to be mismeasured or mistaken for dark matter candidates. As mentioned in Section 1.3.2, the default operating parameters for data taking were set to have a detector temperature of 50 mK with a voltage bias of 70 V applied across the detector. Since occasional fluctuations or instabilities cause the system to deviate from these preset conditions, the operating parameters are recorded on an event-by-event basis and used to identify and remove such events.

Having discussed the event sources and the factors that can impact the data taking, along with the previously covered descriptions of the apparatus and detector, the production of known energies for calibration, and the signal readout and processing, we have concluded our overview of the experimental description of the CDMSlite mode data taking. In the next chapter, we describe the physical processes that occur in the detector in response to an interaction, including the superconducting sensors that are designed to effectively convert the energy into measurable electronics signals for read out. Looking forward to later chapters, we describe the rejection of events that are most likely to be from unwanted sources of data, how we will model the important set of processes in simulation and compare the results to data to see how well we understand the physical processes.

### 3. PHYSICS OF THE CDMSLITE DETECTOR: FROM INTERACTIONS TO SIGNALS

In the previous chapter, we described the CDMSlite detector along with the experimental apparatus that surrounds it, the process for producing the known energy deposits in the detector as part of the calibration procedure, and the data acquisition (DAQ) system. In this chapter we discuss the microphysical interactions and processes underlying the detection mechanisms, focusing on the interactions inside the detector that effectively convert the energy deposit into electronic signals for energy measurement and further analysis, as briefly shown in Figures 1.6 and 1.7. We will cover how interactions can produce electron-hole pairs in the germanium (Ge) crystal of the detector, the generation of additional lattice vibrations (phonons) for signal amplification via an applied voltage, and the subsequent phonon collection that ultimately forms electronic signals. Additionally, we outline the expected total phonon energy to be collected and the physical factors that lead to event mismeasurement when the amount of phonon energy produced is smaller than the expected.

In Section 3.1, we overview the physical properties of the semiconductor and the superconducting components of the CDMSlite detector with an eye toward how an interaction is effectively turned into a measurable signal that can be read out. In Section 3.2, we quantify the responses inside the Ge crystal of the CDMSlite detector to energy deposits, including the expected amount of phonon energy, along with the dominant causes of incomplete energy production; this will often be referred to as an incomplete measurement. In Section 3.3, we describe the set of processes between the phonon generation and the readout electronics that produce the pulse-shape signals like the ones as shown in Figure 2.7a.

#### **3.1 The Semiconductor and Superconducting Components of the CDMSlite Detector**

In this section, we overview the physical properties of the semiconductor and the superconducting components of the CDMSlite detector with an eye toward how an interaction is effectively turned into a measurable signal that can be read out. We first present the big picture of the roles each component has in the process, with more quantitative details about the underlying physics and

processes described in later sections. As shown in Figures 2.2 and 2.3a, the bulk of the detector is a semiconductor constructed as a single crystal of Ge, and the superconducting component consists of aluminum (Al) and tungsten (W) components that are attached to the crystal top and bottom surfaces. An energy deposit in the Ge crystal can produce both charge carriers and phonons, as illustrated in Figure 1.6, while the superconducting components function as phonon sensors that effectively collect phonons and convert their energy into electronic signals for readout.

In Section 3.1.1, we overview the physics of the semiconductor detector material, single-crystal Ge, which, when under voltage, efficiently converts keV-scale energy deposits into phonons that can be collected to form electronic signals. In Section 3.1.2, we overview the components of the superconducting sensors and discuss the physics utilized to enable the conversion of phonon energy into observable electronics signals.

### **3.1.1 The Semiconductor Detector Material: Single Crystal Germanium**

In this subsection, we overview the physics of single-crystal Ge, a semiconductor material, to explain its suitability for use in a detector for dark matter search experiments. For our purposes, its most important property is that it allows for the conversion of keV-scale energy deposits into phonons that can be collected to form electronic signals. In the first paragraph, we summarize the ideas that are most useful for our descriptions of semiconductor properties. In the second paragraph, we describe the crystal properties of the semiconductor that allows for signal amplification via an applied voltage. In the third paragraph, we motivate the particular choice of Ge as a detector material due to its low energy requirement for charge ionization.

We begin by summarizing the ideas that are most useful for our descriptions of semiconductor properties following the descriptions of Refs. [28, 29]. A semiconductor, such as a Ge crystal in the CDMSlite detector, is well-suited for particle detection compared to the other two types of solid materials, metals and insulators, because interaction energy deposited in the material can free electrons to move and produce measurable signals. As shown in Figure 3.1, in atoms in a solid, electrons occupy discrete energy levels: those with lower energies remain bound to atoms and are referred to as residing in the valence band, while those with a high-enough energy are



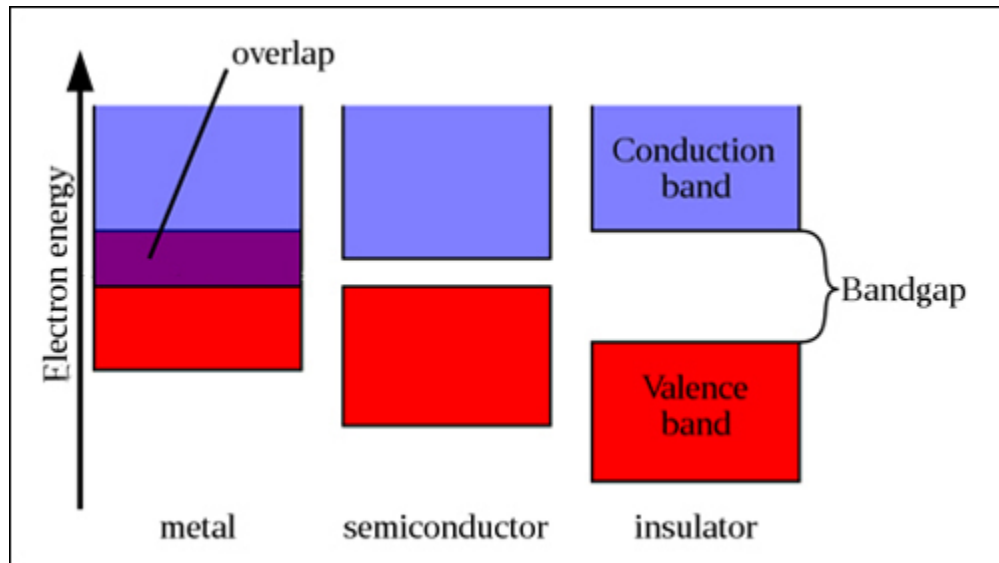


Figure 3.1: This figure shows a cartoon of the allowed energy levels of electrons in three different types of solids. We show it to illustrate the energy required for an electron to readily move through a material and why a semiconductor is a good choice for our detector. When an electron remains bound to an atom we say that it is in the valence band, and when it is able to move freely in the material we say that it is in the conduction band. The energy difference between these two bands is known as the bandgap. Metals, shown on the left, are conductive naturally as its conduction band overlaps with valence band. On the other hand an electron in an insulator, shown on the right, requires significant additional energy to move to the conduction band. In the middle we see a semiconductor which has a small bandgap which means it's naturally non-conductive but an electron can move freely if it receives the small amount of energy needed to excite it to the conduction band. This property makes semiconductors a good fit as a detector material. Figure taken from Ref. [30].

free to move throughout the crystal and are referred to as occupying the conduction band. The energy difference between these two bands, known as the bandgap, distinguishes metals, insulators, and semiconductors. Metals have overlapping bands, allowing large numbers of electrons to move continuously. Insulators have large bandgaps, which means that there are typically very few free-moving electrons. In contrast, semiconductors have small bandgaps: they are normally non-conductive, but when external energy is deposited, such as through a particle interaction, electrons can be excited from the valence band to the conduction band. These electrons are free to move, and can be directed by a voltage in ways that can to produce signals that are proportional to the deposited energy.

The semiconductor crystal properties allows for signal amplification via an applied voltage.

When an electron in the lattice is ionized by an external energy deposit, it leaves behind a vacant position in the outermost energy shell of its parent atom, referred to as a hole, which can move from atom to atom in the lattice and behaves like a particle with a positive charge. The interaction is often referred to as the creation of an electron–hole (e-h) pair, and after they separate, they are often individually referred to simply as charges or charge carriers. Each charge carrier will initially possess kinetic energy and will scatter off the crystal lattice, producing phonons and losing part of their energy, as illustrated in Figure 3.2. In the case where a voltage is applied across the semiconductor crystal, the electric field accelerates the charge carriers so that they continuously gain kinetic energy and emit additional phonons, effectively amplifying the number of phonons produced. With a high enough voltage, a large number of phonons can be generated, providing significant signal amplification. The processes of the e-h pair creation and phonon-mediated signal amplification will be described quantitatively in more detail in the next section.

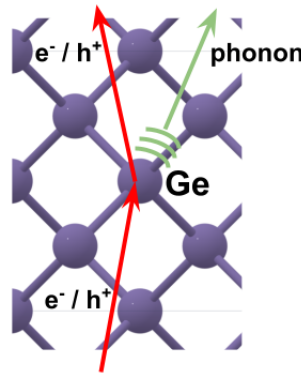


Figure 3.2: This figure shows a diagram of a simplified Ge crystal structure along with trajectories of charges (electrons and holes, indicated by  $e^-$  and  $h^+$ , respectively) and phonons. We show it to illustrate how charges produce phonons in the Ge crystal. Charges with kinetic energy larger than about 30 meV scatter off the lattice and produce phonons. These phonons carry energy and momentum and propagate through the detector. Figure (lattice background) courtesy of Ref. [31].

One advantage of using Ge as a detector material is its low energy requirement for the creation of an e-h pair. Crystals of Ge have a bandgap of 0.67 eV, and the average energy required to ionize

an electron, thereby forming an electron-hole pair, is approximately 2.96 eV [32].<sup>1</sup> This value is lower than those of other commonly used semiconductor materials, such as Si (3.6 eV) and GaAs (4.2 eV), as summarized in Table 2.3 in Ref. [33], which means that more e-h pairs are created per keV, and thus has the potential for a better resolution in the energy measurement.

Having overviewed the properties of single-crystal Ge that make it a powerful detector material, we next overview the components of the superconducting sensors and the underlying physics to better understand how they are used to collect the phonons as part of the energy measurement process.

### **3.1.2 The Superconducting Sensors: Quasiparticle Trap Assisted Electrothermal Feedback Transition Edge Sensor (QET)**

In this subsection, we overview the components of the superconducting sensors and discuss the physics utilized such that they enable the conversion of phonon energy into electronics signals. As shown in Figure 3.3, the Al and W superconductors are fabricated together to function as phonon sensors attached to the crystal surfaces, and known as Quasiparticle Trap-Assisted Electrothermal Feedback Transition-Edge Sensors [34], or QETs for short, for reasons we will describe shortly. The Al component covers a surface area, known as a Al fin, which absorbs phonons and transports their energy to the W component. The W components are fabricated into wires which are integrated into a voltage circuit, and known as Transition-Edge Sensors (TES). Both are designed so that their detailed superconducting and electrical properties are utilized for phonon energy measurement. In the first paragraph, we overview the superconducting properties that underlie the operation of the Al fins and W wires in the QETs. In the second paragraph, we describe the microphysical processes occurring in the QETs via which phonon collection is converted into signal production.

The electrical properties of a superconductor can change sharply at low temperatures. At room

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<sup>1</sup>We note that the 2.96 eV is larger than the bandgap. The bandgap is defined as the smallest difference between the valence and conduction bands. However, for Ge, since the conduction band minimum and valence band maximum occur at different points in momentum space, electron excitation across the bandgap requires not only additional energy but also a change in momentum, which causes the creation of a phonon. See more details in Chapter 8 of Ref. [29]. We also note that if the electron and hole are not created with enough kinetic energy they can immediately recombine. Thus, ionization energy reflects the average number of pairs produced as a function of incident energy.

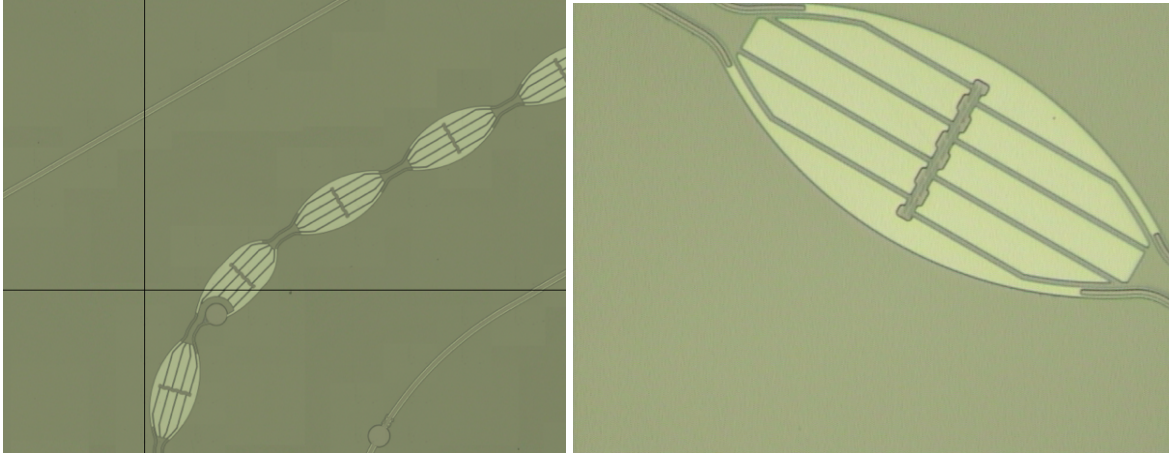


Figure 3.3: This figure shows two photos of real QET units on the surface of the Ge crystal of the CDMSlite detector. Each elliptical structure corresponds to a QET unit. The white regions are the Al components that cover a portion of area to collect phonons, known as Al fins. The central elements are the W wires that produce electrical signals upon phonon collection via the processes illustrated in Figure 3.5. Figure courtesy of the SuperCDMS Collaboration.

temperature, a superconducting material has a non-negligible resistance, known as conductivity. However, as shown in Figure 3.4, below a certain temperature, known as the critical temperature, the resistance effectively goes to zero, known as superconductivity. The region between the two, where the resistance changes sharply from nonzero to nearly zero, is often referred to as the transition region or the transition edge.

The superconducting properties arise from the microphysical behavior of the electrons at low temperatures, and can be used for energy measurement. At room temperature, electrons in superconducting materials can move freely but scatter off atoms, producing electrical resistance. As the temperature cools to below the critical temperatures (e.g., 1.2 K for Al [37]; tens of mK for W, depending on the material composition [38]), electrons can form weakly bound pairs, known as Cooper pairs, which move without scattering and thus eliminate resistance. External energy from particles such as phonons can break Cooper pairs into two excitations that behave like independent particles, referred to as quasiparticles (QPs). One can think of both the temperature and the resistance as being proportional to the number of QPs in the superconductor. By operating a material (e.g., W wires in QETs) near the middle of the transition edge, the system achieves maximum sensitivity: the

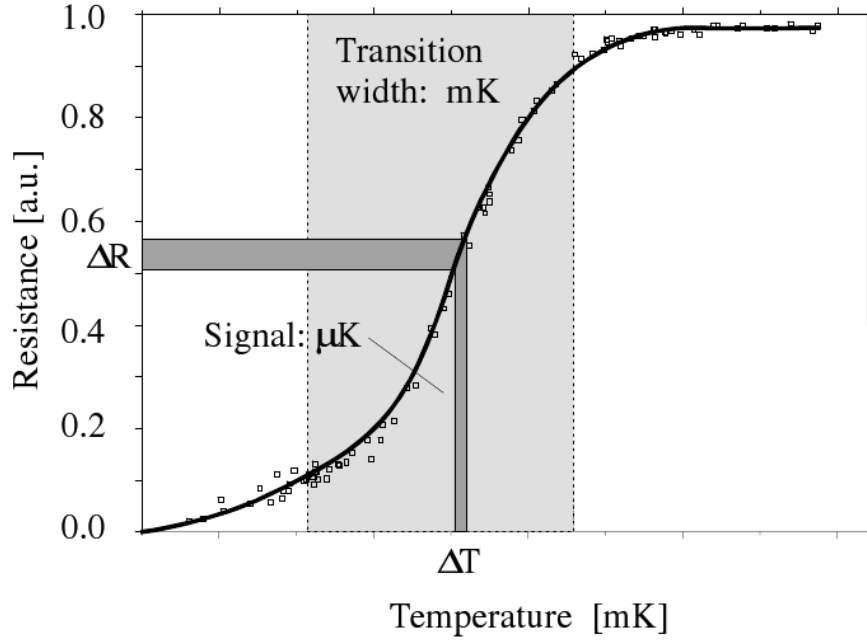


Figure 3.4: This figure shows the resistance of a superconductor as a function of temperature where we have focused on the region where it goes from superconductivity (zero resistance) to conductivity (non-zero resistance). We show it because this small region enables the conversion of phonon energy in a way that allows for an energy measurement. By placing the superconductor on a device and keeping the temperature in this region, known as the transition edge, a small amount of phonon energy can significantly raise the temperature which, in turn, raises the resistance in a readout circuit. This allows us to measure a small energy deposit in the detector. Figure adapted from Ref. [35], and originally from Ref. [36].

heat from a small phonon energy causes a slight increase in the temperature, which in turn produces measurable changes in resistance.

Through the microphysical processes in QETs operated at a low temperature, phonon collection is converted into signal production. The QETs are maintained at a temperature of  $\sim 50$  mK which places the Al fin well-within the superconducting state, but the W wires at their transition edge. As briefly described in the previous subsection and discussed in more detail in Section 3.2.1, a large population of phonons are generated in the Ge crystal due to an interaction, and eventually make their way to the QETs. As shown Figure 3.5, when a phonon impinges on an Al fin, it can break multiple Cooper pairs into QPs that can diffuse into the W wires. Due to the different

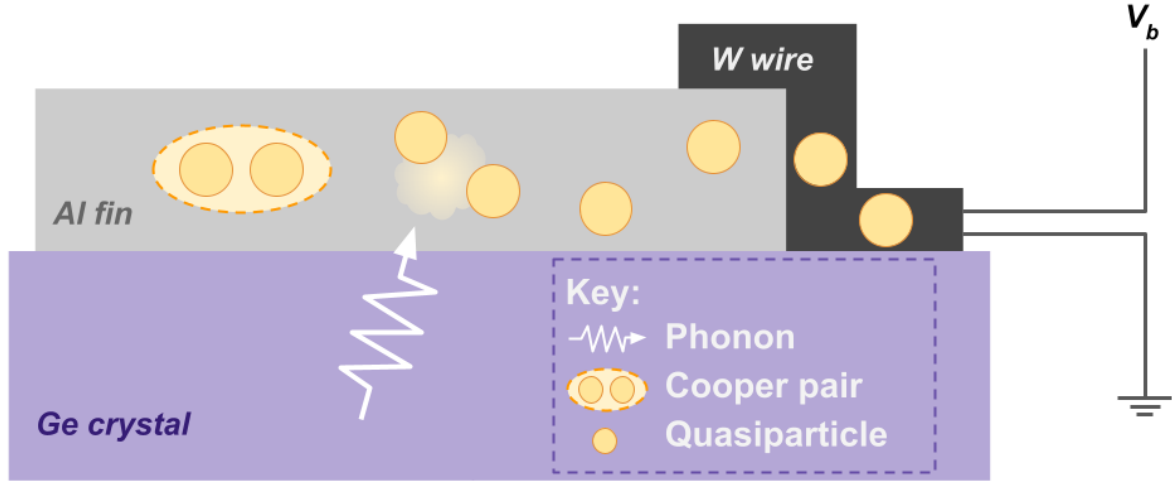


Figure 3.5: This figure shows a cross-section of a single QET unit on an detector surface, many of which form the phonon sensors as shown in Figure 2.3a. We show it to illustrate how phonon energy in the germanium crystal produces a current in the readout circuit. Phonons typically enter the aluminum (Al) fin and break up pairs of electrons, known as Cooper pairs, into quasiparticles (QPs) that can diffuse into the tungsten (W) wires. Due to the different material properties between W and Al, these QPs cannot return to the Al so they are effectively ‘trapped’ in the W wires, which heats up, causing a change in resistance and current in its circuit, as described in Figure 3.4. Figure taken from Ref. [39].

material properties between W and Al, these QPs cannot return to the Al so they are effectively ‘trapped’ [34]. This transfer causes a rise in the temperature and resistance of the W wires. As part of a voltage-biased circuit, this change subsequently results in a measurable current response, commonly referred to as a signal or pulse, which is read out by the readout electronics. More details about the later stages of the process and signal output will be described in Section 3.3.2, and pulse interpretation will be described in Section 4.1.

Having overviewed the semiconductor and superconducting components of the CDMSlite detector and the underlying physics utilized to convert energy deposits into electronics signals for energy measurement, we next quantitatively describe the production of the expected total phonon energy, along with several physical causes that can prevent us from measuring the full complement of the expected energy.

### 3.2 Total Phonon Energy from Electron Recoils

In this section, we quantify the responses inside of the Ge crystal of the CDMSlite detector to energy deposits, including the expected amounts of phonon energy and the dominant causes of incomplete measurement. In this work, we focus on the particle interactions with the atomic electrons, known as electron recoils (ER). As shown in Figure 3.6, ERs are induced by incident particles such as photons and electrons, which can ionize atomic electrons in the Ge lattice and create electron-hole pairs, as outlined in Section 1.3.2 and described in the previous section. While not discussed further in this work, we note that some electrically neutral particles, such as neutrons

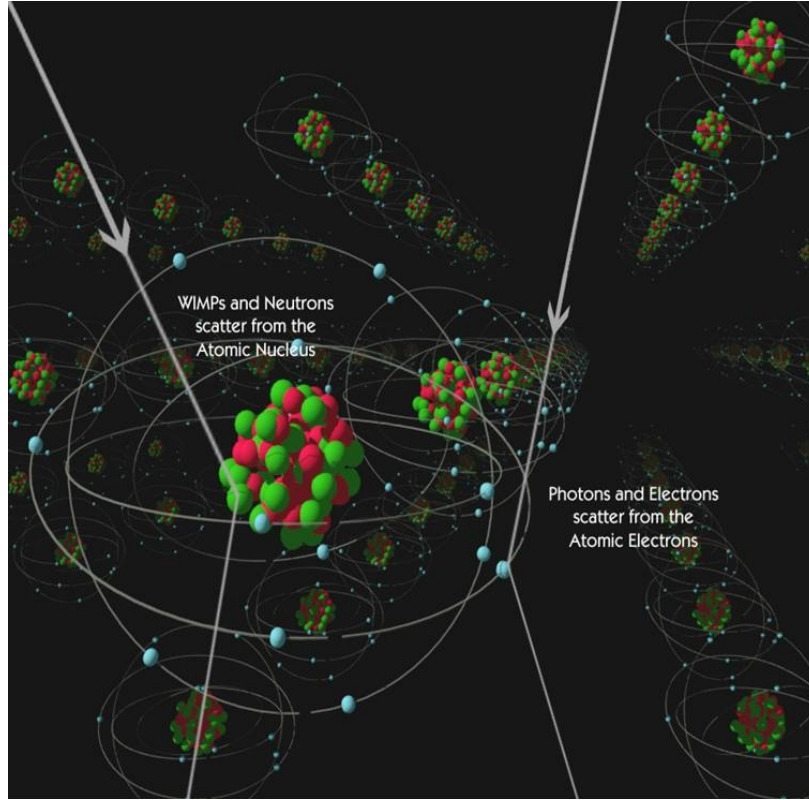


Figure 3.6: This figure shows the same interaction as Figure 1.4, but from the perspective of the atoms in a crystal lattice. We show it because the lattice responds differently to interactions of external particles with the atomic electrons and with the atomic nucleus. The interaction of a photon or electron with an atomic electron is referred to as an electron recoil (ER), and the interaction of a WIMP or neutron with an atomic nucleus is referred to as a nuclear recoil (NR). Figure courtesy of the SuperCDMS Collaboration.

and WIMPs, typically interact directly with the atomic nucleus, known as a nuclear recoil (NR). We choose ERs to serve the goals as described in Section 1.4, as we can reliably identify a clean sample of ER events with well-known energy deposits from the Ge-71 decay during the calibration process, as described in Section 2.2 with more detail in Section 4.3, allowing us to simulate the underlying physical processes and generate results for comparison.

After ionization, any charge carrier produced with enough kinetic energy ( $> 30$  meV for Ge) will collide with the Ge lattice, producing phonons. Additionally, if there is an applied voltage, the charge carriers will continuously pick up energy as they traverse the detector, but then quickly lose some of it by producing phonons when they go above the threshold. This process is known as the Neganov-Trofimov-Luke (NTL) effect [40, 41], and can be thought of as an amplification of the signal produced. In principle, each charge carrier pair traverses the full voltage and if all phonons produced in this process are collected, we can calculate the expected total phonon energy, with which we can work backwards to estimate the energy of the original deposit. In practice, however, there exists several physical factors that can prevent the complete collection of this expected energy.

In Section 3.2.1, we quantify each component of phonon generation that contributes to the final collected energy as charge carriers transport across the detector with an applied voltage and explain how the expected total phonon energy is calculated. In Section 3.2.2, we discuss the four most important factors related to the detector configuration that prevent the expected amount of total phonon energy described in the previous subsection from being collected.

### **3.2.1 Phonon Generation and the Expected Total Phonon Energy**

In this subsection, we quantify each component of phonon generation that contributes to the final collected energy as charge carriers transport across the detector with an applied voltage and explain how the expected total phonon energy is calculated. While there are three stages by which phonons are generated, at high-enough voltages the majority of the phonon energy is from the NTL effect as illustrated in Figure 3.7. The expected total phonon energy is given by the sum of the initial energy deposited by the electron recoil and the extra energy added by the applied voltage. In the first paragraph, we quantify the predictions for the number of electron-hole pairs induced by an ER



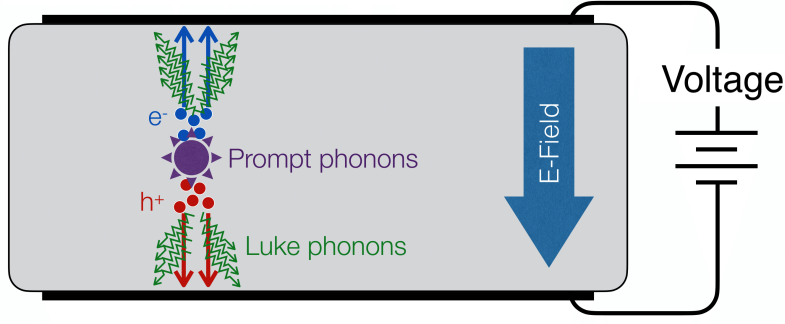


Figure 3.7: This figure shows a cartoon of the initial and subsequent particles produced when an interaction occurs inside the CDMSlite detector. We show it to illustrate how the voltage is able to amplify the amount of energy initially deposited by proliferating the amount of subsequent phonons to make it measurable. Charges (electrons and holes, indicated by blue and red dots) as well as phonons (prompt phonons indicated in purple) are initially produced when an interaction deposits energy into the detector. As charges are pulled by the electric field (blue and red arrows), they both pick up energy and bounce into the lattice and create many more phonons, known as Luke phonons (green arrows). This effect is called the Neganov-Trofimov-Luke (NTL) effect and the energy amplification is used to measure the small amount of energy deposited in the CDMSlite detector, including that possibly transferred from a Weakly Interacting Massive Particle (WIMP). Figure courtesy of the SuperCDMS Collaboration.

interaction. In the second paragraph, we describe the various processes of phonon generation along the charge carrier trajectories. In the third paragraph, we calculate the expected phonon energy from all processes.

Given an energy deposit from an ER interaction,  $E_{ER}$ , it can quickly interact with multiple lattice points ionizing a number of pairs. The number of e-h pairs created,  $N_{eh}$ , in an energy deposit is proportional to the deposited energy, and is approximated by

$$N_{eh} = \frac{E_{ER}}{E_{eh}}, \quad (3.1)$$

where  $E_{eh}$  is the average energy required to create one e-h pair, which is 2.96 eV for Ge [32].

Phonons are generated in three stages, each of which contribute to the total phonon energy produced in an event. The first is that as each charge carrier is created in an ER interaction, it begins with an initial kinetic energy. As this energy is typically above the Luke emission threshold it will

lose some of its initial kinetic energy by producing phonons over a short distance [14]; while there is no commonly accepted name for these, for our purposes we will refer to them as prompt phonons even though that term has been used to describe other things.<sup>2</sup> The second is the NTL effect. The phonons that are generated during this stage, referred to as Luke phonons, have a total energy equal to the applied voltage times the charge, which in this case is  $e$ . The third is that, when the charge carriers reach the detector boundaries, they come to rest and recombine with the lattice, releasing their residual kinetic energy of  $\sim 30$  meV and the Ge bandgap energy of 0.67 eV as phonons; these phonons are referred to as relaxation or recombination phonons.

The expected total phonon energy consists of the contributions from all the prompt phonons, the Luke phonons and the recombination phonons, where the second term is our expected "amplification" term. The summed energy of the prompt and recombination phonons is equal to the initial energy deposited by the electron recoil,  $E_{ER}$ . For a total detector voltage of  $\Delta V$ , using the results of Equation 3.1, the energy carried by the Luke phonons, is given by

$$E_{NTL} = N_{eh}e\Delta V = E_{ER} \cdot \frac{e\Delta V}{E_{eh}}. \quad (3.2)$$

Note that since we have both an electron and a hole, no matter where the pair is produced, between them they are expected to experience the full voltage drop. Therefore, the expected total phonon energy is given by

$$E_{total} = E_{ER} + E_{NTL} = E_{ER} \cdot \left(1 + \frac{e\Delta V}{E_{eh}}\right). \quad (3.3)$$

As only one side of the CDMSlite detector is read out, approximately half of the total phonon energy is measured. For example, for an electron recoil depositing 10.367 keV (the largest energy released by Ge-71 decay) and  $\Delta V = 70$  V (CDMSlite voltage bias), the expected total phonon energy generated inside the CDMSlite detector is  $E_{total} = 255.54$  keV, so the amount of phonon energy measured from the readout signals is expected to be 127.77 keV. Similarly, we can work backwards from the measured phonon energy to determine the amount of energy deposited using

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<sup>2</sup>The term, prompt phonon, has been used to describe the phonons produced in NR interactions as the impact causes the nucleus to vibrate causing phonons.

Equation 3.3. We note in advance that the energy deposit simulated in the samples used in this work is 10 keV, corresponding to an expected total phonon energy of 123.24 keV.

With the description of phonon amplification and the expected total phonon energy complete, we next discuss the dominant physical causes that result in collecting less-than-expected phonon energy which directly affects our discovery potential from the detectors.

### 3.2.2 Physical Causes of Less-Than-Expected Total Phonon Energy

In this subsection, we discuss the four most important processes that inhibit the collection of the expected total phonon energy described in the previous subsection. As a charge carrier transports within the detector, it can be absorbed by the detector edges before reaching the electrodes or traverse a voltage smaller than the applied bias, both of which result in fewer phonons being generated than expected. Each factor can systematically reduce the amount of generated phonons and, consequently, impact the interpretation of the interaction. Understanding them will help us mitigate their impact on experimental results by allowing for corrections of any measurements or rejecting affected events. The dominant processes are:

**Reduced Voltage:** When e-h pairs are created at large radii, some of their trajectories traverse regions of reduced voltage near the detector sidewall, as shown in Figure 2.4. These regions, with a triangular-shaped zone, have a voltage drop of <70 V due to the grounded detector housing. Charges passing through this region do not experience the full bias voltage applied across the detector and therefore gain less energy, resulting in a reduced number of Luke phonons. This is expected to be localized to events with large radial distance from the center of the detector, but can be a significant effect when it occurs.

**Off-Electrode Effect:** In principle, when all the electrons and holes are successfully collected at the electrodes, their trajectories span the full applied voltage bias (70V), resulting in the generation of the full expected amount of Luke phonon energy. In practice, as shown in Figure 3.8, some charges reach the surface and are absorbed before reaching the electrodes. In doing so they traverse a voltage drop slightly less than the full applied bias, consequently producing less than the full-expected amount of phonon energy. This is expected to be a small, but observable effect for all

events.

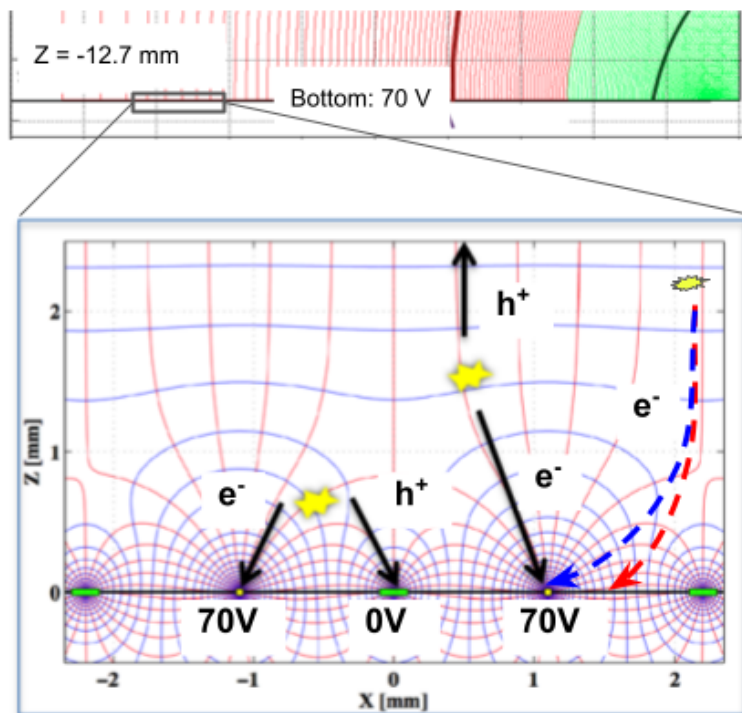


Figure 3.8: This figure shows how the actual paths of charges pulled to the electrodes can cause a small phonon energy mismeasurement. We show it because, in the detector, some charges reach the surface off-electrode without experiencing the full voltage drop and consequently not producing the full expected amount of phonon energy. A simplified version of the trajectory (black arrows) has each charge pulled by the electric field toward the electrodes and getting absorbed after experiencing the full voltage drop. In reality, the speed and impact parameter of the charges can cause some to behave as shown by the blue arrow, while some hit the surface off-electrode as shown by red arrow.

**Surface Trapping:** When an interaction occurs near a detector surface, as shown in Figure 3.9, charges have a finite probability of being absorbed before experiencing any voltage drop. As described above, the typical process, after creation, is that all charge carriers initially travel a short distance (5-10  $\mu\text{m}$ ) in random directions before being directed by the electric field. If a set of charge carriers originates near a surface, some fraction of them will be absorbed by the surface before the electric field can redirect them toward the electrodes, thereby not generating the expected amount of

Luke phonons. We also note that there are scalloped fields around the electrodes. If the interaction occurs near such a location in the field all of the "wrong" charges can be directed immediately to the surface, which will also result in surface trapping. This effect is localized to the top and bottom surfaces, but large when it occurs.

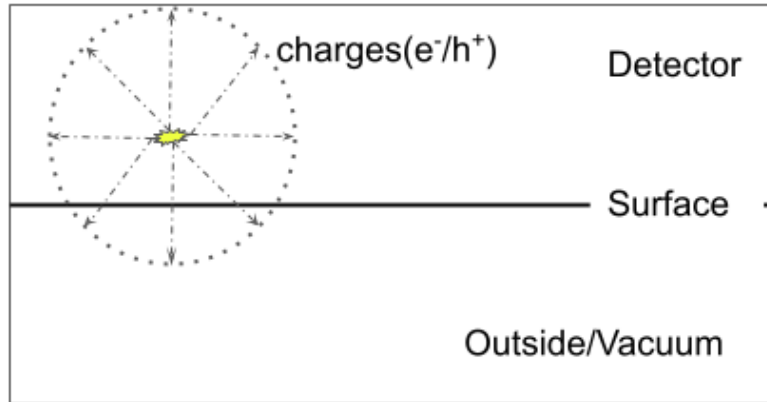


Figure 3.9: This figure shows the case where an interaction occurs very close to the bottom surface of the detector, and the liberated charges quickly travel about  $5\text{-}10\ \mu\text{m}$  randomly before feeling the electric field very much. We show it as another example of a case where a fraction of the charges can get absorbed without creating their full complement of expected phonons which affects the phonon energy measurement. This effect happens for both top and bottom surfaces.

**Sidewall Effects:** When e-h pairs are created near the sidewall, some charges take a path that encounters the detector sidewall, where, for simplicity, we assume they are absorbed, and do not undergo the full voltage drop. As shown in Figure 3.10, charges are driven by the electric field and typically travel toward the detector top/bottom surfaces. However, if an interaction occurs near the sidewall, some charges may strike the sidewall and get absorbed. As a result, these charges traverse only part of the voltage bias and do not generate the expected amount of Luke phonons. Again, this effect is localized to regions of large radial distance from the center of the detector, but the difference between the observed and expected amount of energy can be large when it occurs.

Having discussed the four most important effects that cause the measured phonon energy to be less than expected, along with the previously covered signal amplification via the NTL effect and

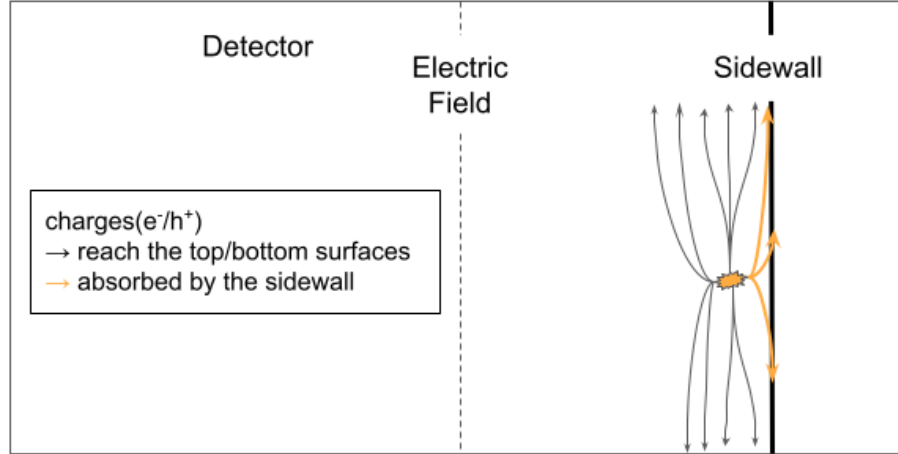


Figure 3.10: This figure shows the trajectories of a number of charges liberated in an interaction that occurs near the sidewall of the detector. We show it because some of the charges (yellow arrows) will interact with, and get absorbed by, the sidewall before they traverse the full voltage, which affects the phonon energy measurement. In this case each such charge will not create their full complement of expected phonons.

the expected full phonon energy, we have completed our discussion of phonon amplification, our expectations for well-measured events and causes of poorly-measured events. In the next and final section, we discuss the phonon bouncing inside the detector and absorption by the superconducting sensors, and how these processes influence the shape of the output signal from the CDMSlite detector.

### 3.3 Phonon Collection Over Time and Sensor Electrothermal Response

In this section, we describe the set of processes between the phonon generation and the production of a signal by phonon sensors like the one as shown in Figure 2.7a. Following their generation, each phonon can scatter as they travel through the Ge lattice and reflect on the detector boundaries before getting absorbed by sensors, as briefly illustrated in Figures 3.11 and 3.12. The time and energy of arrival at the sensors is determined by the phonon speed, the intra-lattice scatterings, as well as the path and the number of reflections on the detector edges. While this determines the input power spectrum to each QET, the final output pulse shape is also determined by the electrothermal response of the sensors. We note in advance that, due to the varying amounts of phonon energy

collected by different channels, the resulting signal shape in each is expected to differ, which will be studied and used in the analysis presented in Chapters 8–10. On the other hand, to a good degree of approximation, the combination of all channels is expected to mostly be consistent since all the phonons are essentially absorbed somewhere.

In Section 3.3.1, we discuss the scattering and reflection processes phonons undergo before being absorbed by the sensors, leading to the phonon collection over an extended time to be characterized by early and late times, also referred to as the fast and slow components. In Section 3.3.2 we describe the electrothermal response of the sensors and how they further shape the electronics readout signal.

### **3.3.1 Phonon Scattering, Reflection and Collection: Fast and Slow Components**

In this subsection, we qualitatively describe the scattering and reflection processes involved in the phonon transport within the Ge crystal of the CDMSlite detector before absorption by the sensors. Based on these processes, we can categorize collected phonons into fast and slow components, and introduce a simplified model to describe these two components; a quantitative study is presented in Section 7.3. In the first paragraph, we overview the phonon scattering process within the detector. In the second paragraph, we describe two reflection modes as phonons reach the detector surfaces before ultimately being absorbed by the sensors. In the third paragraph, we describe the phonon collection as a function of time, consisting of a fast component that is position-dependent and a slow component that is more evenly distributed across the detector. In the fourth paragraph we introduce a new set of labels for the three inner channels (PB, PC, PD) - lead, near, away - based on the relative amounts of phonon energy they collect for later use.

In a single Ge crystal operated at temperature of  $\sim 50$  mK, scattering primarily depends on the energy carried by each phonon [42, 43]. High-energy phonons (frequency  $> 1$  THz or energy  $> 4$  meV) decay almost immediately into lower-energy phonons before they travel very far. Lower-energy (sub-THz) phonons either decay on a timescale of a few microseconds while undergoing multiple random scatterings within a distance of a few millimeters, or they travel over distances comparable to the detector size (on the order of centimeters) before scattering at randomized angles, which

depends on the phonon modes as summarized in Section 2.2.2 of Ref. [44]. In the three stages of phonon generation as described in the previous section, both high- and lower-energy phonons are produced. As a result, at early times after their generation, some phonons rapidly reach the region of the detector surfaces above the interaction position and are absorbed, whereas others arrive later due to scattering processes in addition to reflections as described next.

There are two reflection scenarios as phonons reach the detector surfaces before ultimately being absorbed by the sensors. The phonon sensors attached to the detector's top and bottom surfaces cover only a portion of each surface. As illustrated in Figure 3.11, when a phonon reaches a QET unit, it is either absorbed with a finite probability, or reflected back into the Ge crystal. When striking the sidewall or any uncovered region of the detector surfaces, a phonon is reflected. Some phonons are absorbed during their first encounter with sensors, while others continue scattering and bouncing until they are eventually absorbed, as shown in Figure 3.12. This reflection behavior, along with the scattering process, results in phonon collection occurring over an extended period of time, typically on the order of several milliseconds.

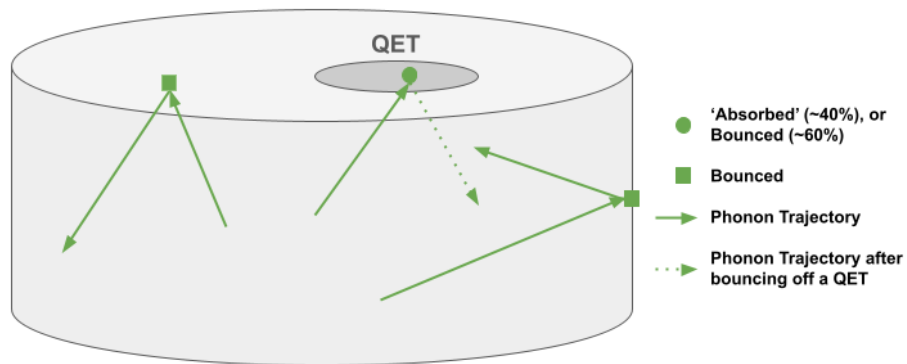


Figure 3.11: This figure shows a simplified diagram of the CDMSlite detector with example phonon trajectories in scenarios of bouncing and absorption. We show it to illustrate that a phonon either bounces back into the detector or gets absorbed by a phonon sensor. When a phonon reaches the top/bottom surface or the sidewall of the detector, it is reflected back into the detector (indicated by a square). When it reaches a phonon sensor, a single QET unit, it is either absorbed with a probability of  $\sim 40\%$  or reflected (indicated by a circle).



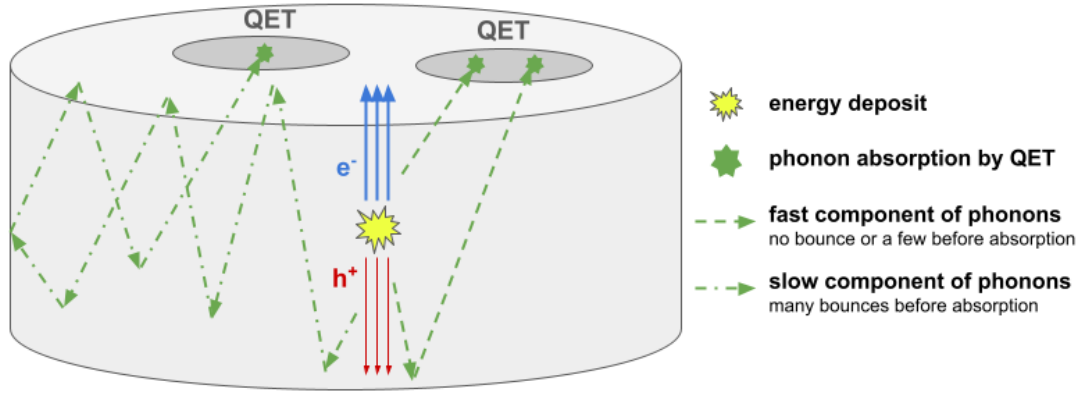


Figure 3.12: This figure shows a simplified version of the detector response combining the styles of Figure 3.7 and 3.11. We show it to illustrate that some phonons are absorbed after zero or a few bounces, defined as the fast component, while others undergo many bounces before absorption, defined as the slow component.

The interaction position determines the phonon collection as a function of time, consisting of a fast component that is position-dependent and a slow component that is uniformly distributed across the detector. As illustrated in Figure 3.12, we refer to phonons that are collected quickly as fast phonons and those that are collected at later times as slow phonons. The fast phonons are expected to be primarily collected by the sensors located directly above the interaction site, whereas the slow phonons are gradually collected by all sensors across the detector surface after multiple scatterings and bounces. Their energies, referred to as Fast and Slow Energy, can be qualitatively approximated by a two-circle model, as shown in Figure 3.13, where a smaller circle centered on the projection of the interaction position represents the distribution of Fast Energy, and a larger circle, equal in size to the detector, represents the distribution of Slow Energy. We will present a quantitative study of the phonon collection over time in Chapter 7.

Given that the fast phonons can be absorbed by one or more channels, we introduce a new labeling convention for the three inner channels (PB, PC, and PD) based on the relative amounts of phonon energy they collect. Due to the uneven sharing of Fast Energy among the three inner channels, illustrated in Figure 3.13, each collects differing amounts of phonon energy. Accordingly, we relabel them as the lead, near, and away channels, corresponding to the channels that collect the

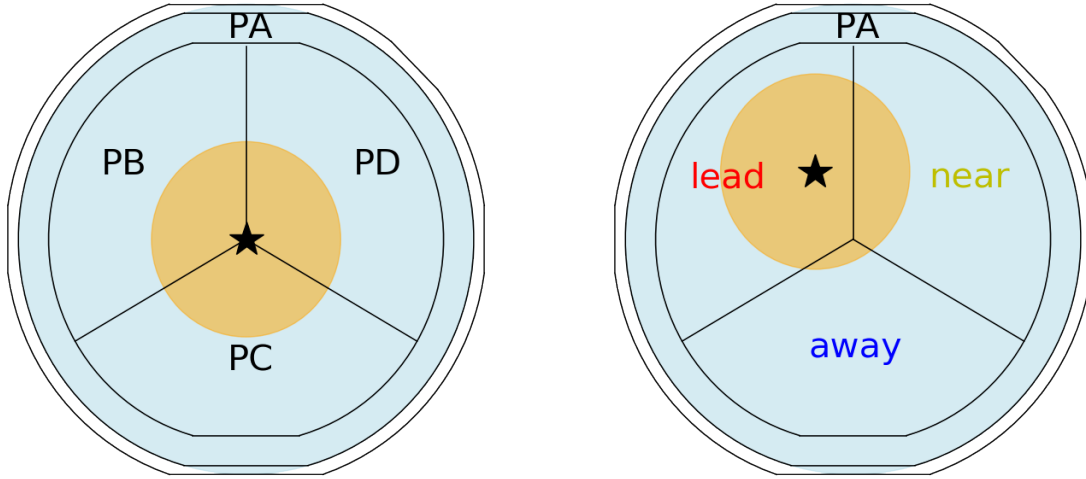


Figure 3.13: This figure shows the simplified two-circle model for two different events where the distribution of the Fast (orange) and Slow (blue) Energy is overlaid on the phonon channel map from Figure 2.3b. In each the interaction position is indicated by a black star and the amounts of orange and blue in each channel illustrate the amount of each type collected by each channel. Note that on the right hand figure, most of the orange is in the channel which is labeled as lead, and we will often use that notation throughout this work. The primary reason we refer to this version of the model as simplified is that Fast Energy is not expected to be uniform in the orange region, although the slow component is effectively modeled as uniform.

most, the second most, and the least amount of phonon energy, respectively. We note in advance that several sets of quantities are constructed using this channel labeling and are employed in the analyses presented in Chapters 8 and 10.

With our qualitative description of phonon scattering, reflection and collection complete, we next describe the overall electrothermal response of the superconducting sensors upon phonon collection, and discuss how the process affects the shape of the resulting electronic signal.

### 3.3.2 The Electrothermal Response of the Superconducting Sensors upon Phonon Collection

In this subsection, we describe the overall response of the superconducting sensors upon phonon collection over time and discuss how the processes affect the shape of the resulting electronic signal.

The signal from the sensors are created as a result of an electrothermal response that includes a circuit as well as heating due to phonon energy deposits and cooling as energy flows back out to the Ge substrate [45, 46]. In the first paragraph, for simplicity, we describe the electrothermal response over time of a phonon sensor upon the collection of a single and two phonons and the cooling provided by the Ge substrate. In the second paragraph we describe the TES response to a typical event in which the input power changes over time. In the third paragraph we describe the similarities and differences between the expected signal shapes from all channels combined and from individual channels.

We begin with the description of the simplest case, as shown in Figure 3.5, in which a single phonon is absorbed by the Al fin of a QET unit and its energy is transferred to its W wires (TES), producing a current signal like the one shown in the top subfigure of Figure 3.14. As part of the experiment, the temperature of the detector is set to be well within the transition region ( $\sim 50$  mK) shown in Figure 3.4, which gives it a finite resistance, and a constant bias voltage is applied which gives a baseline current. When the phonon is absorbed, the TES temperature rises, which results an increase in resistance and a corresponding immediate drop in the current through the readout circuit. Subsequently, due to the temperature gradient between the TES and the Ge substrate, the TES cools back towards the operation temperature, causing the current to gradually return to its baseline. In the case where a second phonon is absorbed before the TES has fully cooled, its temperature and resistance will go up again. To a decent degree of approximation, for low energies, one can think of the output in this case as the sum of two impulses separated but close in time, each with a relative height that is proportional to the energy of each.

The situation becomes more complex in a typical event in which multiple phonons of varying energies arrive over time. After an interaction occurs and a large population of phonons are generated inside the detector, a fraction of them are rapidly absorbed by the sensors which leads to the expected sharp drop, as shown in the bottom subfigure of Figure 3.14; these are the fast phonons. However, phonons continue to be absorbed over time so one can think of the temperature in the TES as being a thermal process in which phonons produce heat and the Ge provides a cooling bath. The

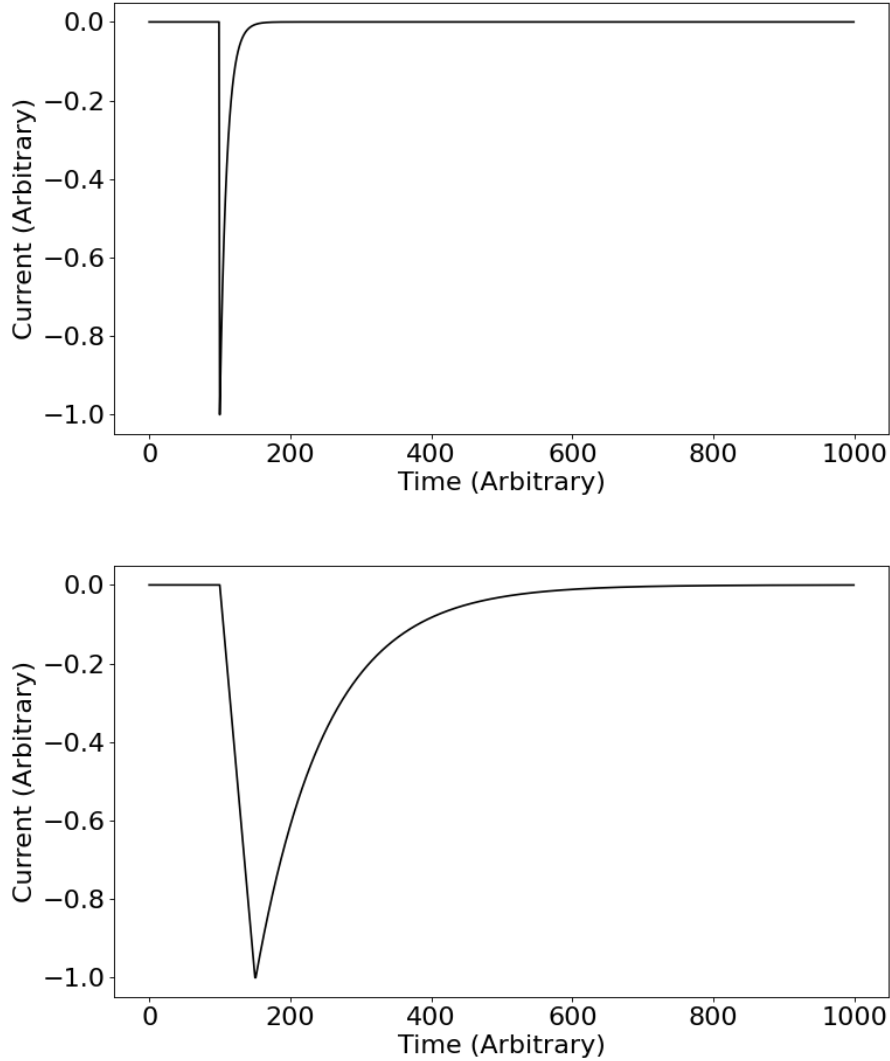


Figure 3.14: This figure shows two toy examples of how the current signals from the TES qualitatively change as a function of time for two different incoming phonon energy absorptions in a sensor. We show it to illustrate the shape of the detector output, a current signal, when phonons are absorbed following an interaction. The top subfigure shows the simplest case when there is a single phonon absorbed, while the bottom subfigure shows the case when multiple phonons are absorbed over time. In both cases, prior to the energy deposit, the TES has a constant resistance and thus the current through it is constant, resulting in a flat line referred to as the baseline.

primary difference from the one-phonon pulse can be seen as the slow phonons continue depositing heat into the sensors with decreasing intensity, while the cooling process dominates, shaping the longer falling part of the signal. Both processes govern the current output, and the full process is well-described by a differential equation with details described in Section 3.3 of Ref. [47].

There are similarities and differences between the signal shapes from all channels combined and from individual channels. Since an energy deposit occurs somewhere in the detector, to a good degree of approximation if we consider all QETs together, we expect the combined signal to be approximately equal on an event-by-event basis. For signals from individual channels, as shown in Figure 3.13, the position-dependent Fast Energy and evenly-distributed Slow Energy will cause similarities and differences in signal shapes like the toy pulses shown in Figure 3.15. As the amount of Fast Energy is collected unevenly among the channels, this results in different leading

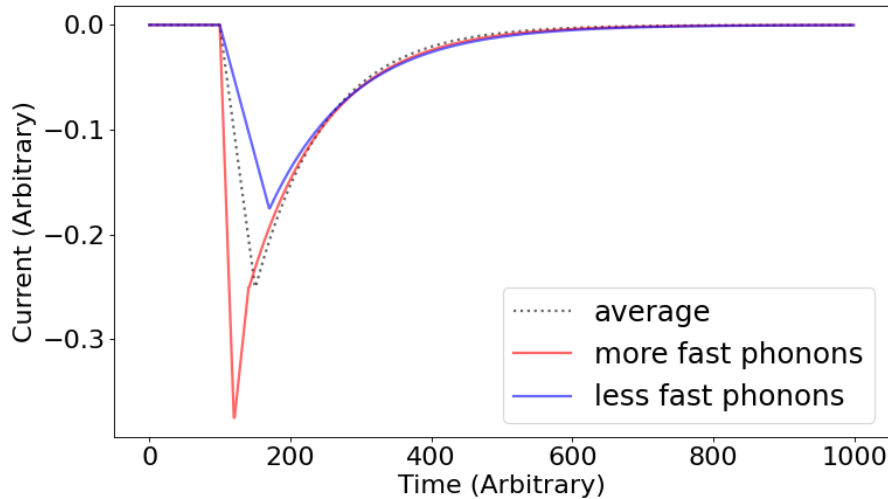


Figure 3.15: This figure shows a toy diagram of how the current through the phonon sensors (the tungsten TES) qualitatively changes as a function of time for two cases: where the channel collects a large portion of fast phonons, and where it collects a small portion; the dashed line shows the average. We show it to illustrate the shape of the detector output, a current signal, when an interaction occurs. As shown in Figure 3.14, the current through the TES starts as a constant before the first phonon arrival after an interaction, and then the collection of phonon energy quickly causes a rise in temperature and so a rise in resistance. Accordingly, the current drops quickly. As the energy is being collected, the temperature is cooled off and so the current returns to the baseline temperature.

edges and peaks in the signals for the four channels. On the other hand, Slow Energy is effectively evenly collected by all channels, leading to consistent relaxation (cooling) portions across channels. We note that these signal shape characteristics, driven by phonon collection dynamics, require different interpretation strategies for signals from combined and from individual channels, and will be described in Section 4.1. Also, these characteristics will be further discussed and utilized for other analysis in Chapters 8–10.

Having presented the sensor output pulse shape of the CDMSlite detector, we have completed our discussion of the aspects of the underlying detector response physics that are most relevant to our work. In the next chapter, we discuss the methods we use to identify events which are likely to be well-measured and recorded during stable data taking that are used for analysis in this work.

## 4. PULSE INTERPRETATION AND EVENT SELECTION FOR ANALYSIS

Previously, in Chapter 2, we described the experiment operation and data-taking process, and in Chapter 3, we discussed the physical processes that occur in the detector, including those that shape the signal out of the detector. In this chapter, we describe the interpretation of pulse shapes using Optimal Filter (OF) algorithms and the selection of events during stable data taking<sup>1</sup> focusing on the rejection of background events, and the identification of 10 keV energy deposit events from the calibration source for analysis in this work.

There are many different ways to derive information from the combination of pulse shapes. Of primary importance is determining whether an event was from an energy deposit and well-measured, which is typically done by confirming that its pulse resembles an expected shape. Equally important is the inference of energy-related quantities, enabling us to select a subset of data suitable for analysis or comparison with simulations. Foreshadowing future work, we note that while the use of OF algorithms on the real data has had successes, and we will use it for the selection of events from the 10.37 keV line from Ge-71 decay, we will use different methods for comparing the sets of events selected in later chapters. This is done as there are discrepancies between the pulse shapes in real data and those from simulations (more detail on these in Chapters 9 and 10); for those studies the analysis methods will be simpler so we can focus on particular aspects of the pulse shapes, allowing the real data to teach us about the simulation and vice versa.

In Section 4.1, we describe how the pulse shapes are interpreted using OF algorithms, known as pulse reconstruction. In Section 4.2, we discuss the selection of the subset of the events taken during stable experimental operation, focusing on the removal of events not relevant to the dark matter search or the calibration process. In Section 4.3, we present the distribution of the pulse amplitudes constructed from the OF algorithms, and describe the final selection of the 10.37 keV electron recoil (ER) events from Ge-71 decay.

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<sup>1</sup>CDMSlite Run 2 data is used for this work.

## 4.1 Interpreting Pulses Using Optimal Filter (OF) Algorithms: Pulse Reconstruction

In this section, we summarize the interpretation of the pulse shapes using OF algorithms, as they provide an estimate of the amount of deposited energy as well as useful information about whether an event originates from a physical interaction and whether it is well measured. We will use a subset of the results from the standard processing used in previous CDMSlite analysis [14] to select events in the next two sections. As discussed in Section 3.3.1, phonon collection over time exhibits both fast and slow components. While the fast component varies from channel to channel, the summed response of the two components from all channels tends to form a consistent pulse shape. When a signal shape and background noise are well understood, OF algorithms can do an excellent job of interpreting the pulse shapes to extract physical quantities. In this case, the total interaction energy can be estimated from the summed pulses across all channels, while the interaction position can be inferred by comparing the fast components of the pulses from individual channels. In the first paragraph, we describe the OF algorithms used for pulse interpretation in the CDMSlite analysis, with a focus on the construction of the expected pulse shapes required for their applications. In the second paragraph, we describe the application of the OF algorithm that uses a single template and accounts for time-varying noise on the total pulse for energy measurement. In the third paragraph, we describe the OF algorithm that accounts for two components in the pulse and provides an attempt to estimate the interaction positions which has been used in the past to reject poorly-measured events.

The OF algorithms are signal processing techniques designed to extract information from noisy pulses in the special case where there are expected signal shapes and noise distributions. It takes in normalized versions of the expected pulse shapes, known as pulse templates, and uses  $\chi^2$  methods to determine best-fit scaling parameters taking into account an expected noise power spectrum distribution (PSD) as shown in Figure 4.1. In our case it returns a best-fit amplitude and the time bin at which the pulse begins to rise, along with a  $\chi^2$  value that quantifies the goodness of fit. Two pulse templates were constructed for use in the CDMSlite analysis: the Average Template and the



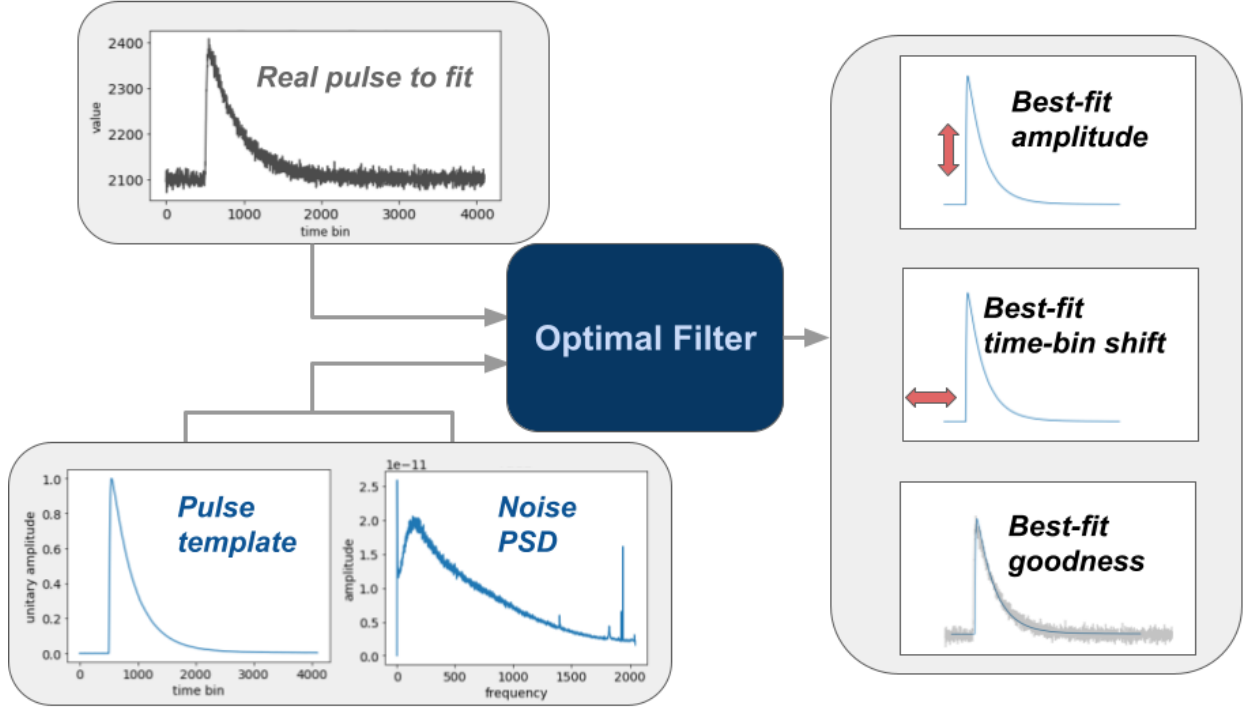


Figure 4.1: This figure shows the inputs, outputs and workflow of the single-template version of the "pulse reconstruction" using the OF algorithm. We show it to illustrate how a pulse is turned into energy measurements and other physically-meaningful quantities that are used for further analysis. This algorithm takes a pulse, fits it using a provided pulse template or two templates, as shown in Figure 4.2, and a power spectral density function representing noise, and returns the amplitude and time offset that minimizes the differences between the pulse and its fit; this difference quantified as a  $\chi^2$  value.

Residual Template,<sup>2</sup> both normalized to have maxima of 1, as shown in Figure 4.2. The Average Template is constructed by averaging the summed pulses from all four channels with high energy deposits, while the Residual Template is constructed by considering the difference between the Average Template and the pulses from individual channels used in its construction [14]. Below, we briefly summarize the application of OF algorithms for energy measurement and position estimation; a more detailed description of the mathematical implementation can be found in Appendix E of Ref. [48].

The best estimate of the energy used in the original CDMSlite analysis is determined using

<sup>2</sup>The Average Template and Residual Template are referred to as the Slow and Fast Templates, respectively, in previous CDMSlite analyses despite that being a bit of a misnomer.

## Templates for Optimal Filter Algorithms

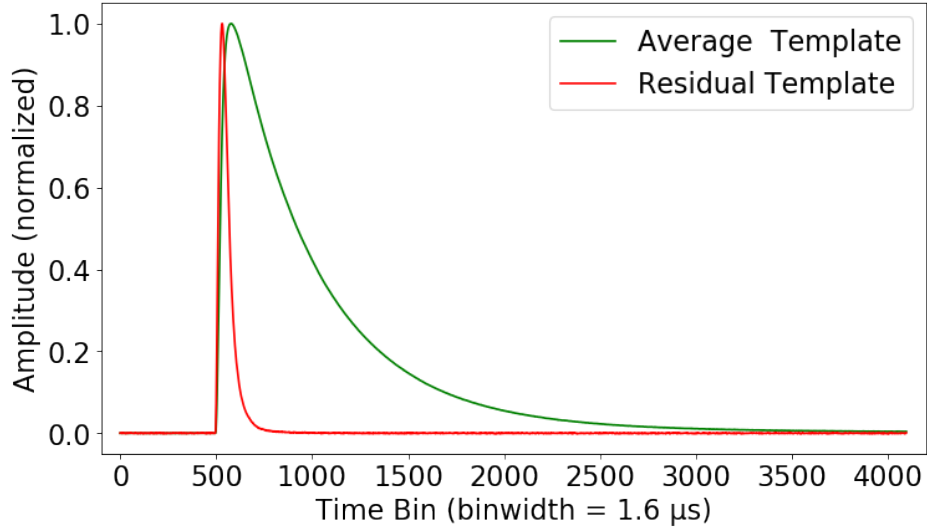


Figure 4.2: This figure shows examples of the two primary types of templates that are used in the CDMSlite OF algorithms: the Average Template and the Residual Template. We show them to illustrate the expected signal component shapes in real data. When considering the summed response from all four channels, the scaled Average Template is a good approximation for the overall shape. However, due to channel-to-channel variations, the response of an individual channel can be approximated as the sum of the Average Template and the Residual Template, each scaled by different factors. The results for an example event are shown in Figure 4.3.

the OF algorithm on the summed pulse from all four phonon channels. This is done with a single template, taken to be the Average Template shown in Figure 4.2, and the time-varying noise. This approach provides both effective noise suppression and an accurate measurement of the signal produced by the interaction. While the amplitude of the best-estimated signal, denoted as PTNFamps,<sup>3</sup> is actually done from the digitized current out of the phonon sensors, this quantity is expected to be proportional to the total phonon energy and is therefore used as an estimator of that energy.

While we don't use it later, we quickly summarize the OF algorithm that accounts for two components in the pulse as it helps point the way towards estimating the interaction position. When both the Average and Residual Templates, shown in Figure 4.2, are included in the fitting procedure

<sup>3</sup>PTNFamps: Phonon; Total signal (summed signal from all four phonon channels); Non-stationary OF; amplitude of the current signal in Amperes.

of individual channel pulses, the combination helps separate out the slow and fast components described in Section 3.3.1. The results for an example event are shown in Figure 4.3. Since, as shown in Figure 3.13, the amount of fast component is determined by the interaction position, this means that the amplitude of the residual component in each channel is a measure of the amount of the fast phonons, offering a qualitative estimate of the interaction position. However, this method was not fully validated as there was no independent way in real data to confirm its correctness (using simulation can help) in the CDMSlite detector. To address this, in Chapter 8 we will present methods to estimate position using pulse shape characteristics in simulation, as discussed in Section 8.3.

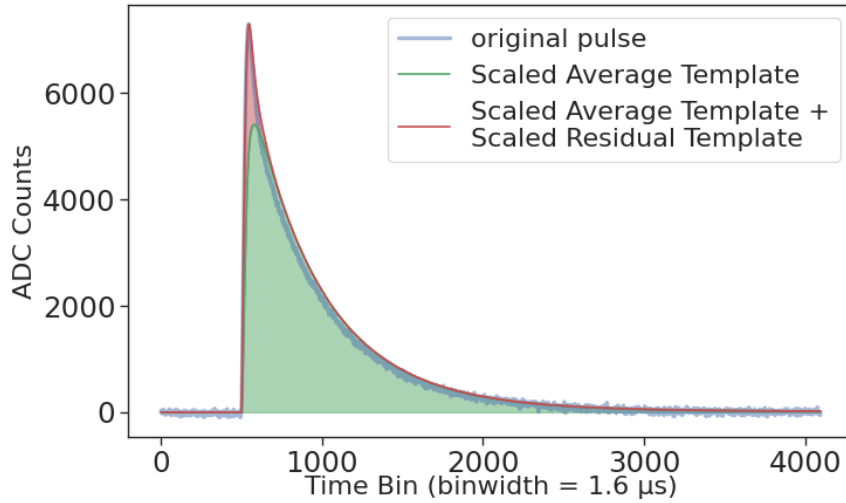


Figure 4.3: This figure shows an example single-channel pulse from the real data along with the rescaled Average and Residue Templates piled up to form the best-fitted pulse by the OF algorithm with two templates. We show it to illustrate the two components separated from the pulses by the OF algorithms.

With our quick overview of the of pulse reconstruction using OF algorithms complete, we now move forward to discuss the selection of events, aided by the algorithm results, during stable data taking and the rejection of background events in the next section.

## 4.2 Selecting Events During Stable Data Taking and Rejecting Background Events

In this section we describe the selection of reliable and useful data. We require consistent experimental conditions as they are crucial to ensure meaningful results as experimental issues such as unstable temperature, voltage fluctuations, electronic noise, and DAQ malfunctions can introduce biases, leading to distorted measurements and false signals. Additionally, since the detector is expected to record interaction events from external particles, such as muons, photons and neutrinos, collectively referred to as backgrounds, these will need to be excluded as they are not relevant to our analysis. By identifying and removing events impacted by these factors, we improve the integrity of the dataset, helping ensure that the extracted physical quantities accurately reflect the underlying physics of the 10 keV ER events we want to focus on.

The criteria developed in the original data analysis [14] to select a reliable dataset for study are mostly used for this work with a few exceptions that we will point out. As listed in Table 4.1, a total of 15 criteria were developed for CDMSlite Run 2, and we include a description of the type of events it removes. For this work, we note that Criterion #14, which attempts to exclude events occurring at larger radii for the reasons described in Section 3.2.2, is not applied in this work, as we aim to include events from the entire detector volume for use in our studies. The final criteria to select events with the energy deposit of 10.37 keV is described in the next section.

## 4.3 Selecting 10 keV Electron Recoil Events for use in Analysis

In this section, we discuss the selection of the subset of events with a 10 keV energy deposit in the real data for use in the comparison with simulation results in later chapters. We remind the reader that the 10 keV energy deposits in the real data are expected to be dominated by ER events from a K-shell Ge-71 decay during the calibration procedure and are used in this work which focuses on studying the CDMSlite detector's response to ERs. As described in Section 4.1, the best-fit value of PTNFamps is expected to be proportional to the total phonon energy distribution and contain three peaks from Ge-71 decay, from which we can identify and select the one corresponding to a 10 keV energy deposit. In the first paragraph, we describe the differences between the distributions

Table 4.1: This table summarizes the criteria developed in the original analysis for selecting quality-event data in CDMSlite Run 2 [14] for use in analysis. We have included it for completeness to describe which events are removed/selected and why in the process. We note that criterion #14 was used in the original analysis but is not applied in this work, as we aim to study events occurring throughout the entire detector.

| #   | Selection Criteria of Reliable Data                                                                                                                                                                                                      |
|-----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1   | Select only events when the bias voltage is 70.0 V                                                                                                                                                                                       |
| 2   | Remove events within 200 $\mu$ s of the expected time of a NuMI (Neutrinos at the Main Injector beam at Fermilab) beam [27] interaction in the detector cavern                                                                           |
| 3   | Remove any data taking series which appear to have electronics issues as indicated by a much larger-than-expected number of events rejected by the phonon pre-pulse standard deviation requirements and charge $\chi^2$ cuts (#5 and #6) |
| 4   | Remove events where the readout electronics were unintentionally or incorrectly activated by noise, timing errors, or faulty components, rather than by an actual interaction (known as misfirings or glitches)                          |
| 5   | Select events where the pre-pulse for all phonon channels are consistent with noise                                                                                                                                                      |
| 6   | Remove events where the charge $\chi^2 > 8585$                                                                                                                                                                                           |
| 7   | Remove events that have drastic difference ( $> 17$ s) between GPS time and DAQ event time                                                                                                                                               |
| 8   | Remove events where the temperature, current or current amplitude are out of tolerance                                                                                                                                                   |
| 9   | Remove events that are read out at random times, unrelated to an energy deposit                                                                                                                                                          |
| 10  | Remove events that may be due to muon interactions from a cosmic ray as identified by the muon veto system of the apparatus                                                                                                              |
| 11  | Remove events that have more than one pulse during the readout window (pile-up events), saturated events, and events that have unusually high noise present                                                                              |
| 12  | Remove events where the pulse shape deviates significantly from the expected shape (the Average Template shown in Figure 4.2)                                                                                                            |
| 13  | Remove events with where the pulse is consistent with low frequency noise in the system                                                                                                                                                  |
| 14* | Remove events where there is evidence that the interaction occurred at large radius, close to the sidewall of the detector, where phonon energy is poorly-measured                                                                       |
| 15  | Remove events identified as having energy deposits in more than one detector in the tower                                                                                                                                                |

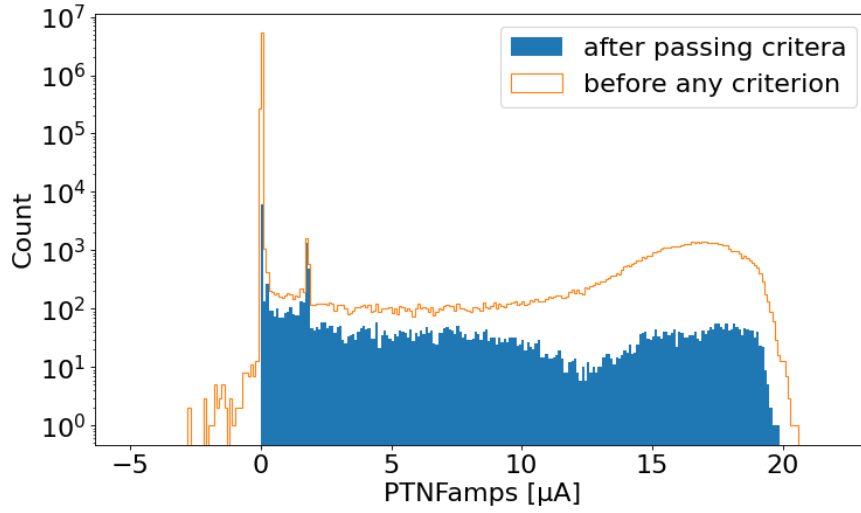
of PTNFamps in the real data before any criterion and after passing the criteria listed in Table 4.1 (#14 not applied in this work). In the second paragraph, describe how we quantitatively select the events corresponding to the 10.367 keV energy deposit from Ge-71 decay using a Gaussian fit. In the third paragraph, we qualitatively comment on the purity of the sample.

The distribution of the measured PTNFamps values for full set of events selected by the DAQ during the selected data-taking periods are shown in Figure 4.4a both before and after the selection criteria in Table 4.1. A large portion of events across the full range are removed, including those with unphysical negative PTNFamps values. The remaining events are considered to have been recorded during stable experiment operation, with reduced influence from the background sources described in Section 2.4. Figure 4.4b shows the distribution of PTNFamps for events in the lower energy region. While there are clearly events from numerous background sources and the sample is dominated by events from noise, the energy deposits from the three energies from Ge-71 decay are readily observed.

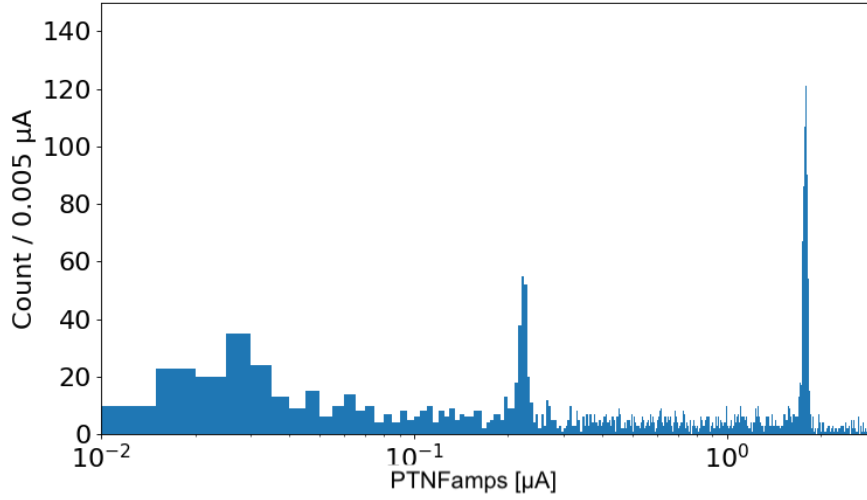
We select the events with energy deposit of 10.37 keV for use in this work. Figure 4.5 shows the subset of events that pass all the cuts for the region around the deposits that produced the highest of the three peaks, which is attributed to the K-shell decay. A Gaussian fit to the peak yields a mean ( $\mu$ ) of  $1.78 \mu\text{A}$  and a standard deviation ( $\sigma$ ) of  $0.03 \mu\text{A}$ , giving a fractional resolution ( $\sigma/\mu$ ) of 1.7%. Based on this result, we select events with PTNFamps values in the range  $[1.72, 1.84] \mu\text{A}$ , corresponding to a  $2\sigma$  window, for comparison with simulated data presented in later chapters.

We note that the selected sample is qualitatively quite pure. The peak from which the events are selected stands well above the surrounding background, as shown in Figure 4.5, supporting the conclusion that the majority of these events originate from ERs induced by Ge-71 decay. However, a small fraction of events contribute from background contributions or mismeasurements of higher-energy deposits in ways that are not symmetric around the peak. As the origin of individual events cannot be determined with certainty, we do not make quantitative statements about the sample purity.

Having completed our discussion of the selection of the subsample of events which are expected



(a) PTNFamps distribution (full range) before and after selection criteria



(b) PTNFamps distribution (zoom-in) for events passing the selection criteria

Figure 4.4: This figure shows two versions of the distribution of PTNFamps (the estimated amplitudes obtained by the OF algorithm with non-stationary noise as described in Section 4.1) for the sample of events collected during the CDMSlite Run 2 data-taking period; one before and one after passing the criteria listed in Table 4.1. We show it because this quantity is proportional to the deposited energy in an event, and the sample of events illustrates the response to the the full set of sources in the data. The top plot shows the full spectrum range before any criterion and after passing criteria, and the bottom plot shows a zoomed-in version which contains the three peaks corresponding to the three energies released by Ge-71 decay as as shown in Figure 2.6 and listed in Table 2.1. The events in the highest peak at the rightmost contains the sample of events selected for this work, with selection details shown in Figure 4.5.

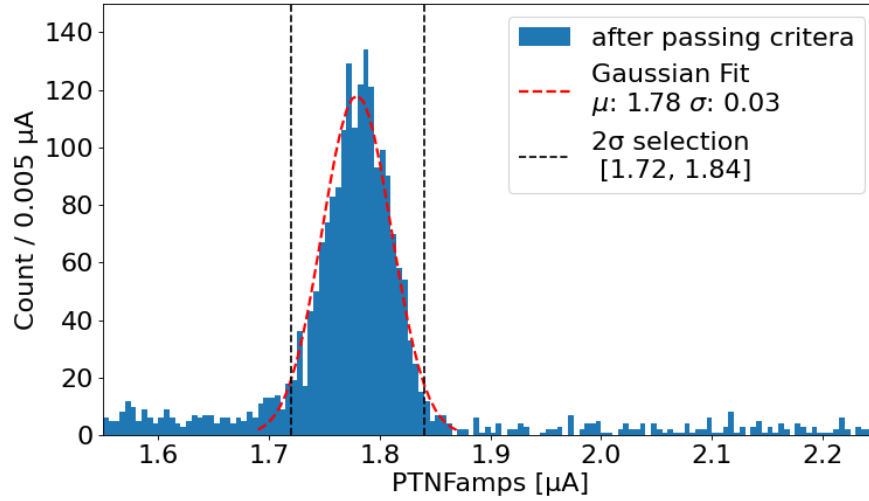


Figure 4.5: This figure shows the zoom-in version of Figure 4.4b but focusing on the highest peak corresponding to the 10 keV energy deposit from Ge-71 decay. We show it to illustrate the subset of events selected for comparison to simulated data in this work. The two dashed lines indicate the  $2\sigma$  region around the peak, and represent the final event selection criteria of  $1.72 < \text{PTNFamps} < 1.84 \mu\text{A}$ .

to be a fairly pure sample of ER events with a 10 keV energy deposit, we are ready to compare these results with simulations. In the next chapter, we transition to the description of the simulations by describing the infrastructure and the samples made from it. We will return to comparisons in later chapters.



## 5. SIMULATION OF THE CDMSLITE DETECTOR’S RESPONSE AND SAMPLES

Previously, in Chapters 2 - 4, we discussed the relevant details about the SuperCDMS experiment and the CDMSlite detector, covering the experiment apparatus and operation, the detector physics utilized to convert interactions into signals, and the subsequent data processing and event selection. As a reminder, the goal of this work is to deepen our understanding of the CDMSlite detector’s response through simulation and comparison to experimental data. In this chapter, we overview the simulation infrastructure, and describe how we simulate the CDMSlite detector’s response, as outlined in Figure 1.7, to mirror the discussions in previous chapters. We also introduce the simulation samples created with 10 keV electron recoils, used as a simple approximation of Ge-71 decay for use in the comparisons for pedagogical reasons as it removes unneeded complexity which allows us to evaluate the impact of various processes. We note at the beginning that many of the details predate this work and are described well in Ref. [44] so we will not give additional citations unless it is from somewhere else.

In Section 5.1 we overview the main components of the SuperCDMS simulation infrastructure. In Section 5.2, we describe the three simulation samples used in the analysis along with how each helps us understand the CDMSlite detector’s response.

### 5.1 Overview of the SuperCDMS Simulation Infrastructure

In this section, we overview the SuperCDMS simulation infrastructure, which consists of two main components: SourceSim, which models energy depositions, and DetectorSim, which simulates the detector’s response as well as the data acquisition processes, as illustrated in Figure 5.1. The simulation chain is implemented and handled by the software framework for the SuperCDMS experiments, SuperSim, which is built on the combined Geant4 [49, 50, 51] toolkit which is integrated with the custom Geant4 for Condensed Matter Physics, G4CMP [44] package. It ultimately produces events in the same format as the real experimental data so they can be processed and analyzed in the same way. We note in advance that while not all the components in the figure

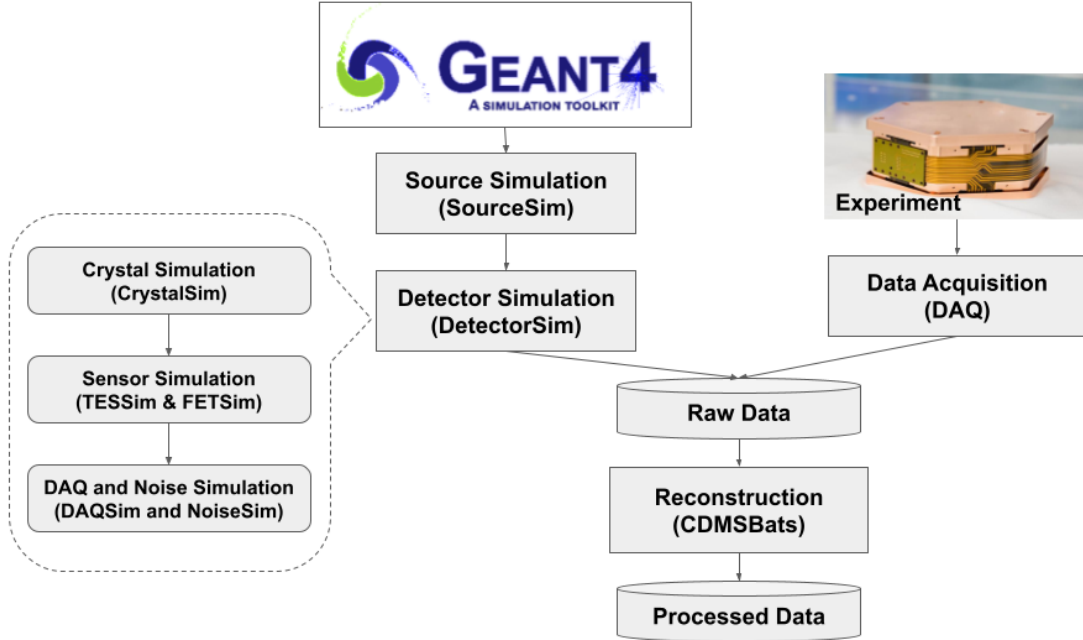


Figure 5.1: This figure shows the main components of the simulation infrastructure. We show it to illustrate how the simulation workflow mirrors the real data taking and reconstruction process. Starting on the top left, the simulation of energy deposits and incoming particles is done within Source Simulation which is often referred to as SourceSim. The output is then sent to the next simulation stage, simulation of the subsequent particle propagation in the detector and readout, Detector Simulation which is referred to as DetectorSim. DetectorSim consists of three submodules that implement the Crystal Simulation, Sensor Simulation, and Data Acquisition (DAQ) simulation (including noise modeling.) Both SourceSim and DetectorSim are implemented using the Geant4 and G4CMP toolkits. The output of DetectorSim is referred to as Raw Data, and has a format designed to be identical to the output from the real detectors. The conversion of the pulse shapes into measured quantities for both simulated and real data is done within the Reconstruction software, referred to as CDMSBats, which produces the processed data for further analysis. Figure courtesy of the SuperCDMS Collaboration.

are utilized in this work, we overview their functionality for completeness. In the first paragraph, we overview SourceSim which simulates particles that travel through things and eventually hit the detector, or interactions that directly occur in the detector. In the second paragraph, we overview DetectorSim which takes the output of SourceSim and models the response of the semiconductor and superconductor components of the detector, as well as the data acquisition processes.

SourceSim, the first stage of the SuperCDMS simulation, simulates particles that travel through things and eventually hit the detector, or interactions that directly occur in the detector. SourceSim

has the ability to simulate various sources, such as WIMPs (the dark matter candidate described in Section 1.2), Ge-71 decays (the source providing energies for calibration as described in Section 2.2), photons and electrons (incident particles causing electron recoils as shown in Figure 3.6), or idealized interactions (such as nuclear and electron recoils). The output of SourceSim is the idealized interaction type, energy and positions of energy deposits in the detector. For this work, all events are simulated to have the same source, 10 keV energy deposits with only electron recoil interactions, that mimics interactions from photons and electrons emitted by Ge-71 decay.

DetectorSim, the second stage of the SuperCDMS simulation, takes the output of SourceSim and models the response of the semiconductor and superconducting components of the detector, as well as the data acquisition processes, as outlined in Figure 1.7 and described in Chapter 3. While not all parts are used in this work we note that, as shown in Figure 5.2, DetectorSim consists of three submodules:

- Crystal Simulation, CrystalSim, which models the semiconductor crystal's response to energy deposits which includes the creation and propagation of charges and phonons inside the crystal,
- Sensor Simulation, TESSim&FETSim, which models the responses of phonon and charge sensors upon collection of phonons and charges, including the signal generation from the sensors,
- DAQ and Noise Simulation, DAQSim&NoiseSim, which models the data acquisition processes and produces events in the same format as real data, enabling consistent downstream processing and analysis, as shown in Figure 5.1.

For this work, the detector is modeled as a single germanium crystal at low temperature as shown in Figure 2.2 within CrystalSim; more details about the dimensions are summarized in Appendix A. CrystalSim takes the 10 keV electron recoil events and creates a set of electron-hole pairs where the average number of pairs is given by Equation 3.1. The charge and phonon propagation processes, as well as TESSim&FETSim, are modeled in conjunction with G4CMP. In TESSim the thermal and

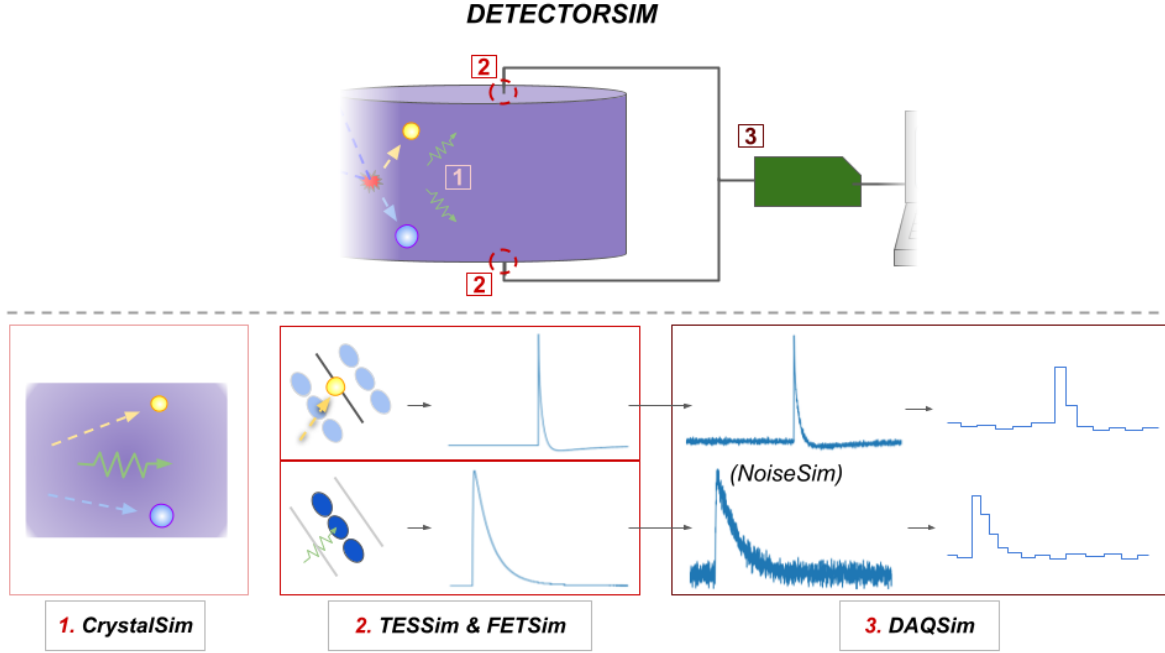


Figure 5.2: This figure shows more details about the DetectorSim processes in Figure 5.1. We show it to illustrate the processes, inputs and outputs within each submodule. Simulation of the detector crystal’s response to interactions, CrystalSim, simulates charges and phonons moving through the lattice from the original energy deposition to the detector edges. Simulation of the phonon sensors on the detector top/bottom surface, TESSim, converts phonon energies into current pulses. Simulation of the charge electrodes on the detector top/bottom surface, FETSim (not used in this work), reads the amount of charge collected on the FET circuits and outputs the corresponding charge pulse. Simulation of the data acquisition system, DAQSim, converts analog signals into digital form, rescales, and adds noise (optionally). The scaling and digitization in this figure is exaggerated for illustration. Figure taken from Ref. [39].

electrical dynamics of the QETs are simulated using coupled differential equations (TES\_ODE). Since there are a number of physical parameters used as part of the differential equations, listed in Table B.2, a tuning process was used to make the outputs match the results from the Average Template shown in Figure 4.2. We note that FETSim and NoiseSim are not used for this work. In DAQSim, the signal processing that occurs in the real world, as described in Section 2.3, is mimicked by a series of numerical operations that convert the current signals from the detector into pulses in ADC counts, as shown in Figure 2.7.

Having overviewed the key components of the SuperCDMS simulation infrastructure, we move forward to describe the simulation samples created for this work.

## 5.2 CDMSlite Simulation Samples

In this section, we motivate and describe the three simulation samples used in this work. Since our primary goal is to understand the detector response throughout the volume, we create two samples where the events are uniformly distributed within the detector so we can study the response as a function of position. Since the voltage across the detector causes multiple effects, one version is made with a uniform electric field while the other is made with the realistic electric field model. Comparisons between the two allows for estimates of the impact of these effects. Finally, we create a sample where we can look at how and where each phonon is absorbed by an individual sensor as a function of time to provide us with intuitive and qualitative ways of predicting the outcome for an individual event.

There are both common aspects and variations between the simulation samples to achieve these goals. In each, to enable comparison with the  $\sim 10$  keV peak observed in real data, as shown in Figure 4.5, all simulation samples are generated using electron recoils with 10 keV energy deposits with a voltage bias of 70 V using the software packages listed in Table B.1. For quantitative study of the causes behind less-than-expected phonon energy collection, as described in Section 3.2.2, we create two samples of events uniformly distributed throughout the detector volume, but with two different electric field models. For the phonon propagation and absorption over time, as described in Section 3.3.1, we simulate a single event at the center of the detector.<sup>1</sup>

In the first paragraph, we describe the sample with a uniform electric field inside the detector (UniE sample) without electrodes, designed to investigate the total collected phonon energy and to understand the impact of charge absorption on the sidewalls and surface charge trapping effects as illustrated in Figures 3.9 and 3.10. In the second paragraph, we describe the sample with the realistic electric field model (EPot sample) with electrodes used to study the impact on the phonon energy collection from the off-electrode effect shown in Figure 3.8 and the position-dependent electric field as shown in Figure 2.4. In the third paragraph we describe a variant of the EPot sample with one interaction at the center of the detector, referred to as the EPot\_hits sample, which records the time,

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<sup>1</sup>Other samples like this were generated and studied. Each is presented in Appendix C.

position, and energy information for each phonon absorption by a phonon sensor to understand the phonon collection over time as described in Section 3.3.1.

**UniE sample:** This sample is created with a uniform electric field with no electrodes present. It is used to investigate the response in the channel readout and to study the impacts on the phonon energy collection from the sidewall absorption and the surface trapping effects, as illustrated in Figures 3.9 and 3.10. Following the prediction of Equation 3.3, the total phonon energy is expected to be 123.24 keV for the set of events where all the charges traverse the full voltage drop, but significantly lower for the few that are impacted by sidewall absorption and surface trapping.

**EPot sample:** This sample is identical to the UniE sample except that it is created with a realistic electric field model. It is used to further investigate the impacts on the phonon energy collection from the reduced voltage region and off-electrode effects as illustrated in Figures 2.4 and 3.8, as well as to study the pulse shape from the phonon channels in later chapters. This sample uses the realistic electric field model as shown in Figure 2.4, which was created by finite-element simulation using COSMOL MULTIPHYSICS® software (COMSOL, Inc., Burlington, MA), with electrodes present.

**EPot\_hits sample:** This sample is a variant of the EPot sample that contains only one event with an interaction at the center of the detector, but records the time, position, and energy information for each phonon absorption by the individual phonon sensors rather than on a channel-by-channel basis. It is used to understand the phonon bouncing and collection over both surface position and time, as described in Section 3.3.1. The related analysis and discussion will be presented in Chapter 7.

Having described the CDMSlite simulation samples, along with the CDMSlite experiment and selected data covered in the previous chapters, we are now ready to move forward with the analysis and comparison between the simulation and real data. In the next chapter, we begin by comparing the collected phonon energy and the pulse shape in simulation to our expectations.

## 6. COMPARING PHONON ENERGY COLLECTION AND PULSE SHAPE TO EXPECTATIONS

In previous chapters we described the microphysics of interactions within the CDMSlite detector, the expectations for macrophysical detector responses, the SuperCDMS simulation infrastructure and the simulation samples we created for this work. From this chapter through Chapter 10, we present results from our simulations and compare them to both expectations and real experimental data where applicable, demonstrating a deepened understanding of the CDMSlite detectors response to interactions.

In this chapter, we begin the comparison process by focusing on both the total phonon energy collection and the shapes of the pulses from the combined and individual channels, referred to as total and individual pulses. As described in Section 3.2, we have quantitative expectations for the total amount of energy collected on the top surface, as well as a number of mismeasurement causes which can reduce that amount. Given that the expectations for the amount of collected phonon energy is position dependent, we refer to those physical regions where the total phonon energy of an event is well-measured as being the fiducial region; other locations are referred to as the non-fiducial region. We use both the UniE and EPot samples, as described in Section 5.2, to quantitatively separate between well- and poorly-measured events, illustrate the impact of the various causes of energy mismeasurement, and determine the shape of the fiducial region. Comparing the pulse shape of an event from the EPot sample to the expected shape, the Average Template, allows us to evaluate their similarities and differences. As we will see, the collected phonon energy in simulation is basically consistent with the expected value and the differences can be explained by the four physical factors (reduced voltage, off-electrode effect, surface trapping, and sidewall effects) described in Section 3.2.2. While the total pulse shape is close to the expected shape, some differences are observed, which will be further investigated in Chapters 9 and 10.

In Section 6.1 we compare the distributions of the collected phonon energy in the UniE and EPot samples to the expected value as a way to define well- and poorly-measured events, as well

as measure the impact of the off-electrode effect. In Section 6.2 we compare regions of well- and poorly-measured events in both samples to expectations, to identify regions from the other three causes. In Section 6.3 we provide preliminary comparisons of the simulated pulses to the expected shapes.

## **6.1 Comparing Simulated Total Phonon Energy to Expectations: Well- and Poorly-Measured Events**

In this section, we compare the distributions of the total collected phonon energy from the UniE and EPot sample to the expectations from Section 3.2.1, and use them to define well- and poorly-measured events. As we will see, on average the off-electrode effect reduces the total phonon energy collection by approximately 2% so we will have slightly different criteria for each. We note that the other three causes will be discussed in relation to the regions of well- and poorly-measured events in the next section. In the first paragraph we define the collection efficiency and how it is used to separate between well- and poorly-measured events. In the second paragraph we define the quantitative criteria for separating between well- and poorly-measured events in the UniE and EPot samples. In the third paragraph we compare the peaks of the collection efficiency distributions between UniE and EPot samples.

The collection efficiency is defined as the ratio of the collected phonon energy in simulation to the expected value; in our case this is 123.24 keV as presented in Section 3.2.1. The total collected phonon energy for the UniE and EPot samples are shown in the top subfigures of Figures 6.1 and 6.2, respectively. Since most mismeasurements occur in the outer regions of the detector volume, as described in Section 3.2.2, we expect that most events exhibit a collection efficiency close to 1.00, forming a dominant peak in the distribution, with a small portion having a collection efficiency significantly less than 1.00 due to the various mismeasurement causes. Their distributions allow us to readily separate between well- and poorly-measured events with a simple cut on the collection efficiency.

The collection efficiency for the two samples are shown in the bottom subfigures of Figures 6.1 and 6.2. We note that in the UniE sample, the dominant peak in the collection efficiency is consistent



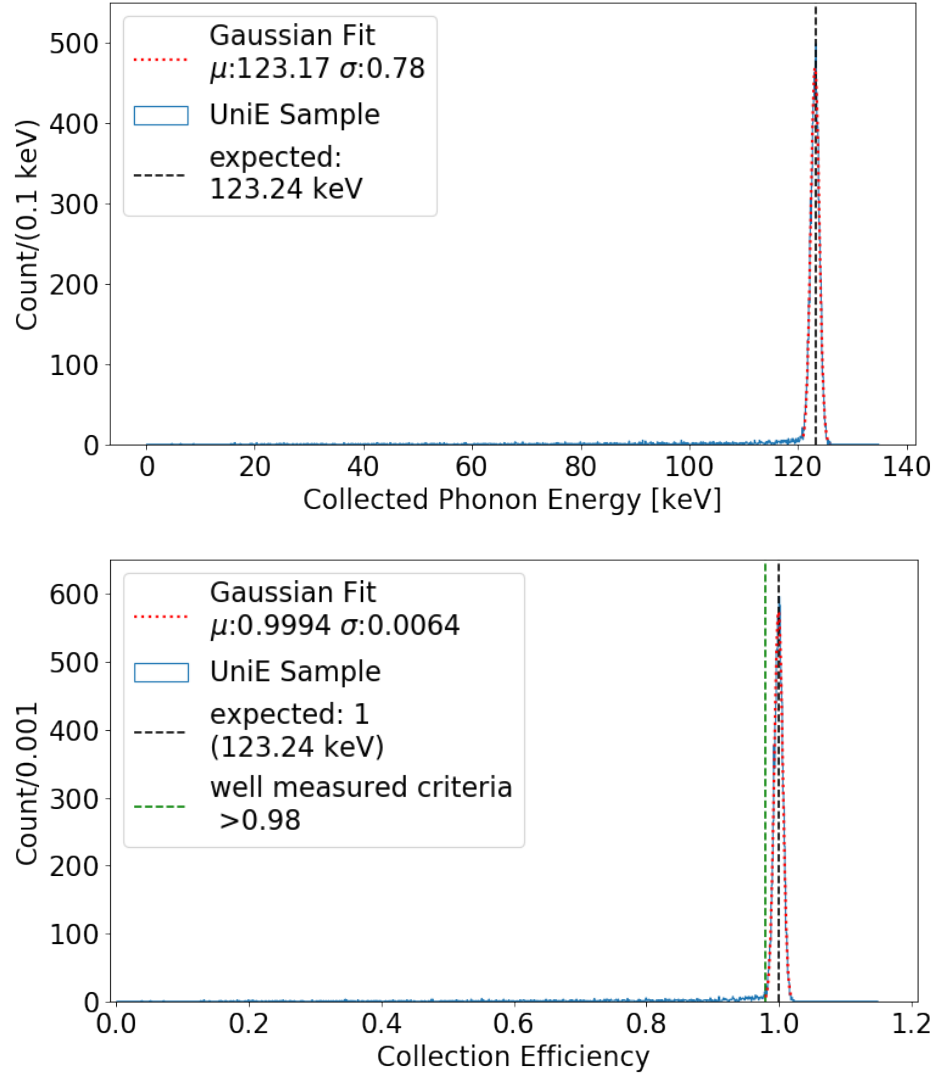


Figure 6.1: This figure shows two plots that indicate the amount of total collected phonon energy as well as a comparison to expectations for the simulation sample with a uniform field (UniE sample). We show it to indicate the differences between well- and poorly-measured events when many of the electric field effects are removed. The top shows the sum of the measured phonon energy from all four phonon channels along with the expected value of 123.24 keV (black dashed line) for a single ER interaction with an energy deposit of 10 keV. The bottom plot shows the ratio of the measured to the expected, referred to as the collection efficiency. In both cases there is a large peak corresponding to well-measured events along with a Gaussian fitted curve (red dotted line) to just the peak region; the poorly measured events are scattered on the left side of the plots. The mean of the collection efficiency peak for well-measured events is 1.00 within uncertainty, and shows a resolution ( $\sigma$ ) of 0.006. The figure also indicates the  $3\sigma$  criteria ( $\geq 0.98$ , green dashed line in the bottom subfigure) used to separate between well-measured and poorly-measured events.

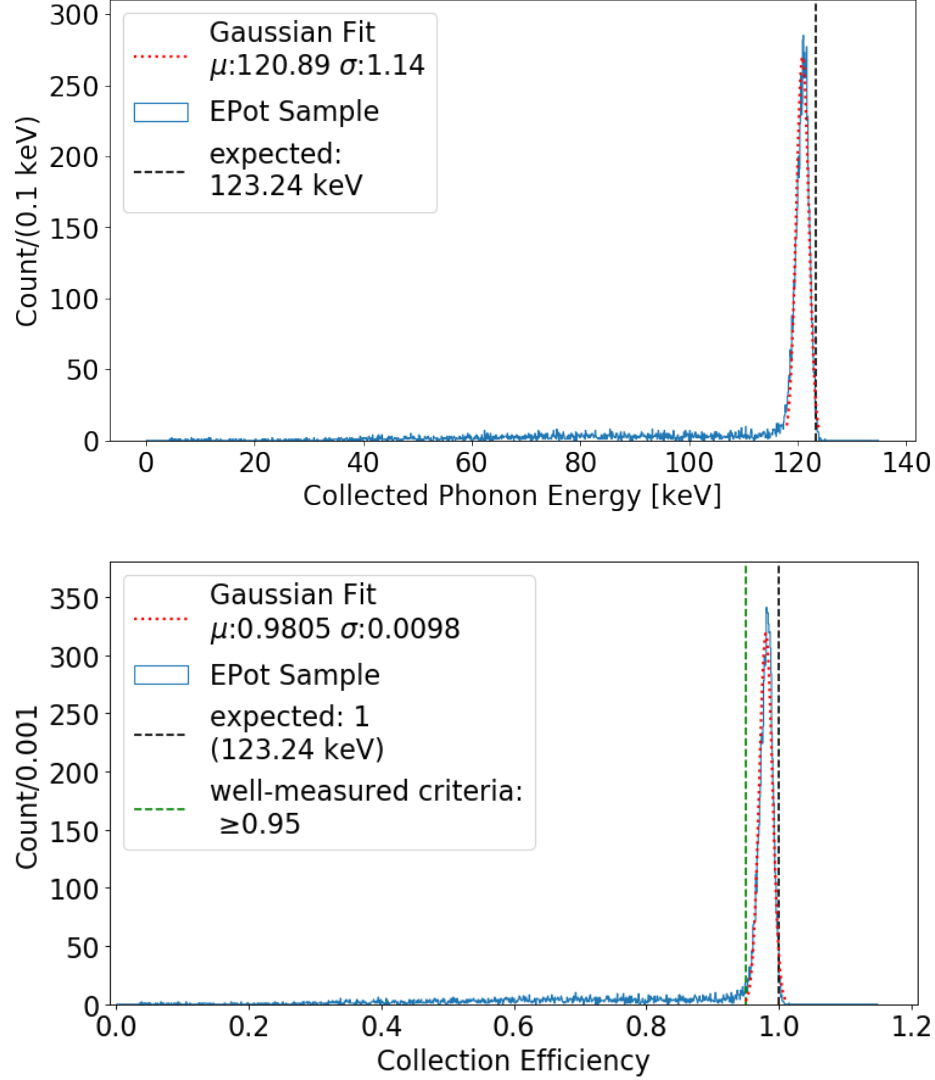


Figure 6.2: This figure shows the same set of plots as Figure 6.1 but for the simulation sample with the realistic electric field model (EPot sample). We show it to indicate the differences between well- and poorly-measured events when the realistic electric field and electrodes are included. With these effects included we find that the collection efficiency for well-measured events is 0.98 with resolution ( $\sigma$ ) of 0.01. The figure also indicates the  $3\sigma$  criteria ( $\geq 0.95$ , green dashed line in the bottom subfigure) used to separate between well-measured and poorly-measured events.

with 1.00; it is centered at 0.9994 with a standard deviation ( $\sigma$ ) of 0.0064. Since events within this peak are considered to have collected the full expected energy, we define poorly-measured events as those with collection efficiency below  $3\sigma$  standard deviations from the peak,  $< 0.98$ , and well-measured events as those with efficiency  $\geq 0.98$ . For the EPot sample, we again see a dominant peak that corresponds to what we would call a full measurement, but is slightly lower as expected from the impact of the off-electrode effect. The dominant peak in collection efficiency is centered at 0.9805 with a standard deviation ( $\sigma$ ) of 0.0098. we apply a similar approach and define poorly-measured events as those with collection efficiency  $< 0.95$  and well-measured events as those  $\geq 0.95$ .

By comparing the means of the dominant peaks of the collection efficiencies in these two samples (almost 1 for UniE and about 0.98 for EPot), we estimate that, on average, we lose approximately 2% of the phonon energy collection due to the off-electrode effect. We also see that the resolution worsens by about about 50%; from about 0.6% (UniE) to about 1% (EPot). The remaining three causes of mismeasurement are discussed in the next section.

Having presented the collection efficiency variable for use in separating well- and poorly-measured events, and having used it to estimate the impact of the off-electrode effect by comparing the results from the UniE and the EPot samples, we next move to illustrate and quantify the expected and observed regions of the well- and poorly-measured events in the same samples and discuss the impacts of the other three mismeasurement causes.

## **6.2 Comparing Regions Where the Total Phonon Energy is Well- and Poorly-Measured: Fiducial and Non-Fiducial Regions**

Since, as described in Section 3.2.2, we expect that the primary reasons events are poorly-measured are correlated with the position of the energy deposit, in this section we present the expected fiducial and non-fiducial regions and the simulated results for the UniE and EPot samples. In the first paragraph, we describe the expected fiducial and non-fiducial regions. In the second paragraph, we compare the results from the UniE and EPot samples with the expectations.

Following the description in Section 3.2.2, the qualitative expectations for the shapes of the

fiducial and non-fiducial regions are shown in Figure 6.3. In the UniE sample, the expected non-fiducial regions are located close to the top/bottom surfaces of the detector and near the sidewall, resulting from the surface trapping and sidewall effects as illustrated in Figures 3.9 and 3.10. In the EPot sample, where there is a reduced electric field as illustrated in Figure 2.4, we expect an additional triangle-like non-fiducial region near the sidewall. We note that this region fully overlaps with the area affected by sidewall effects.

The selection criteria to separate the well- and poorly-measured events from the previous section are used to identify the fiducial and non-fiducial regions in the UniE and EPot samples. The results are shown in Figures 6.4, aligning well with expectations as shown in Figure 6.3. In the UniE sample, poorly-measured events affected by surface trapping occur almost at the detector surfaces, while those influenced by sidewall effects are mostly located at  $R > 37$  mm, with some at  $34 < R < 37$  mm corresponding to the flats of CDMSlite detector as shown in Figure A.2. In the EPot sample, poorly-measured events appear not only in the same regions as in the UniE sample but also in an additional area associated with reduced voltage. This additional region has a triangle-like shape, with its lower edge extending to  $R \approx 29$  mm, in agreement with the reduced electric field shown in Figure 2.4.

Having compared the simulation results of the fiducial and non-fiducial regions to expectations we have completed our comparison of phonon energy measurement, including the impact of each of the causes of poorly-measured events. In the next section, we compare the simulated pulse shape with its expected form.

### 6.3 Comparing Simulated Pulse Shapes to Expectations

In this section, we start the process of comparing the pulse shapes to expectations, considering both the total pulse and individual pulses. While the total pulse is not expected to always be the same on an event-by-event basis, the variations are expected to be small and the average shape of the well-measured pulses is expected to be that given by the Average Template shown in Figure 4.2. On the other hand, the individual pulses are expected to exhibit significant variations in shape characteristics, as shown in Figure 3.15, due to the position dependence of the Fast Energy distribution. As we will

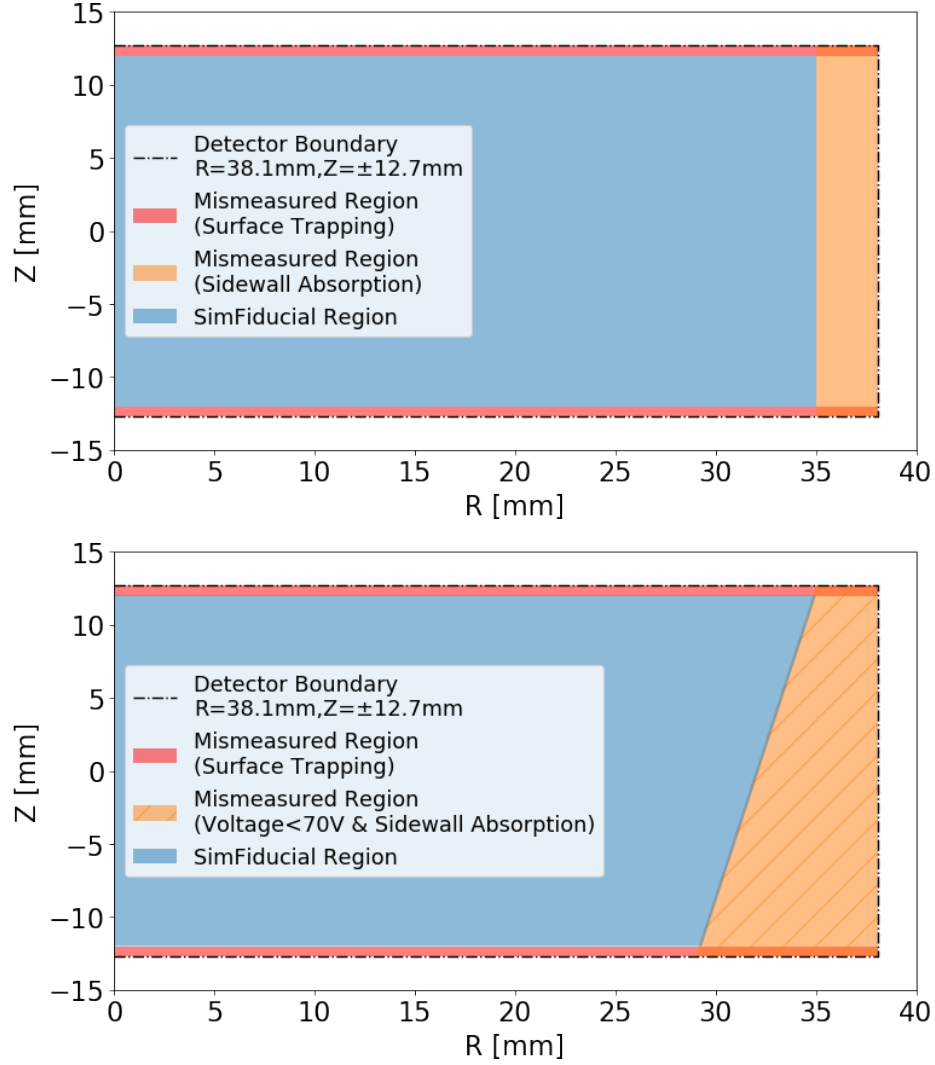


Figure 6.3: This figure shows two simplified diagrams of the regions where we expect events to be well- and poorly-measured (fiducial and non-fiducial regions) with the two different electric field models. We show it for use in comparisons with the simulation results and to help understand the cases of where we do not get the full compliment of expected phonon energy. The top plot shows the expectations for the UniE sample with a uniform electric field and the bottom for the EPot sample with a realistic electric field model. The light blue indicates the expected fiducial region. The long and narrow regions in red very close to the top/bottom surface are where phonon energy is expected to be poorly-measured due to the surface trapping effects shown in Figure 3.9. The light yellow region in the top plot is where the phonon energy is expected to be poorly-measured because of sidewall absorption as shown in Figure 3.10. The hatched light yellow region in the bottom plot is due to the additional effect of the reduced voltage as shown in Figure 2.4. We note that many of these regions overlap with each other.

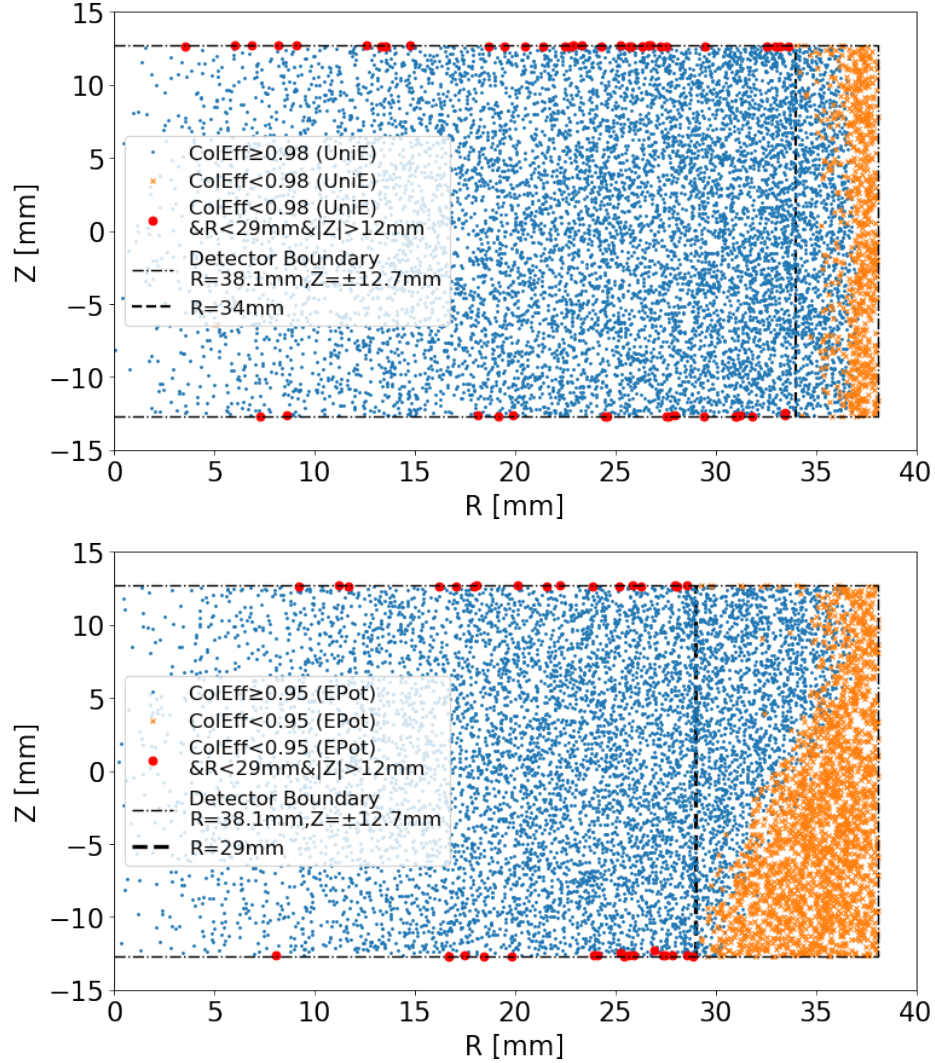


Figure 6.4: This figure shows the interaction positions of events in the  $ZR$  plane for the UniE and EPot samples, where the color code from Figure 6.3 has been modified to additionally indicate the subset of events that are poorly-measured at the top and bottom surfaces. We show it because the color at each position indicates the regions where events in both samples are well- or poorly-measured and allows for a comparison with Figure 6.3. The well-measured events (collection efficiency  $\geq 0.98$  for the UniE sample and  $\geq 0.95$  for the EPot sample) are denoted with blue dots, and the poorly-measured events (collection efficiency  $< 0.98$  for the UniE sample and  $< 0.95$  for the EPot sample) with yellow crosses or red dots. The red dot events have been artificially separated based on their location very close to the top/bottom surface, to indicate those mismeasurements caused by surface trapping. The yellow cross events, near the sidewall of the detector, are caused by the sidewall effects only for the UniE sample, but extend to lower  $R$  when the reduced voltage regions is simulated in the EPot sample.

see, the simulated total pulse qualitatively agrees with the template, though small but systematic discrepancies are observed, whereas the simulated individual pulses only qualitatively align with the expected characteristics. In the first paragraph, we compare the simulated total pulse from an example well-measured event to the Average Template. In the second paragraph, we present the simulated individual pulses from the same event for first comparison; more detailed comparisons will be given in Chapters 9 and 10.

For the total pulse, while it is expected that there will be variation between events for multiple reasons, there is value to comparing a single selected event to see the detail. The event was selected randomly but exhibits a well-measured energy, and the total pulse shape is normalized such that the peak has a value of unity like for the Average Template. As shown in Figure 6.5, the simulated pulse visually has excellent overlap with the template, but with noticeable deviations at the beginning and end. The pre-pulse region (bins  $< \sim 500$ , or time  $< \sim 800 \mu\text{s}$ ) of the simulated pulse is zero due to the absence of noise in the samples used in this work. A bin-by-bin comparison reveals systematic differences in the early part of the pulse ( $500 < \text{bins} < 1000$ , or  $800 < \text{time} < 1600 \mu\text{s}$ ) and in the far tail (bins  $> 3500$ , or time  $> 5600 \mu\text{s}$ ), as shown in Figure 6.6, for reasons that are not clear. As both will have a negligible effect on our analysis we don't consider this issue further.

For individual pulses, we do not expect a single shape like the Average Template as shown in Figure 4.2, but instead variations that reflect a combination of Fast and Slow Energy. The results, as shown in Figure 6.7, qualitatively have the expected shape characteristics of the sensor signals. These two example pulses display different rising edges due to varying amounts of Fast Energy, but share a similar falling region that aligns with the template until the pulse end.

As we come to the end of this chapter we note that our simulated results show good qualitative agreement with our simplest expectations. While there is currently no way to validate the size and shapes of the fiducial regions in the real data, we have presented estimates of the impacts of four physical processes which lower the collection efficiency. Perhaps more importantly, the simulation suggests that the assumption that there is a well-measured region in the detector is well-justified, and while we may not know exactly what it is, by selecting events in the peak of

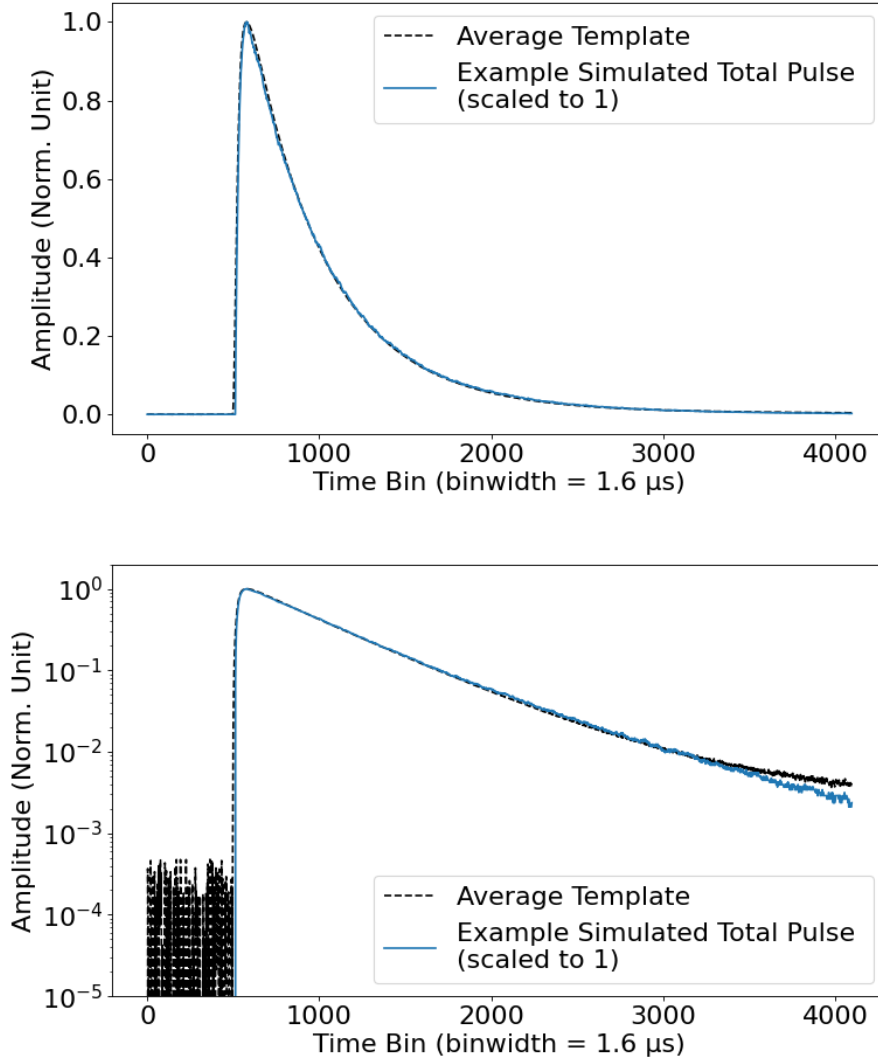


Figure 6.5: This figure shows two versions of a total pulse, one from a well-measured event in simulation along with the Average Template for comparison. We show it to visualize the similarities and differences between them. The simulated pulse has been normalized to have a maximum of 1 to match the Average Template for comparison. Each pulse consists of 4096 bins, with a bin width of  $1.6 \mu\text{s}$ . The top plot uses a linear scale, while the bottom employs a logarithmic scale. Although the simulated pulse aligns well with the template qualitatively, notable quantitative differences are observed at early times because the simulation doesn't include noise effects as well as differences in the tail region, which are further examined in Figure 6.6.



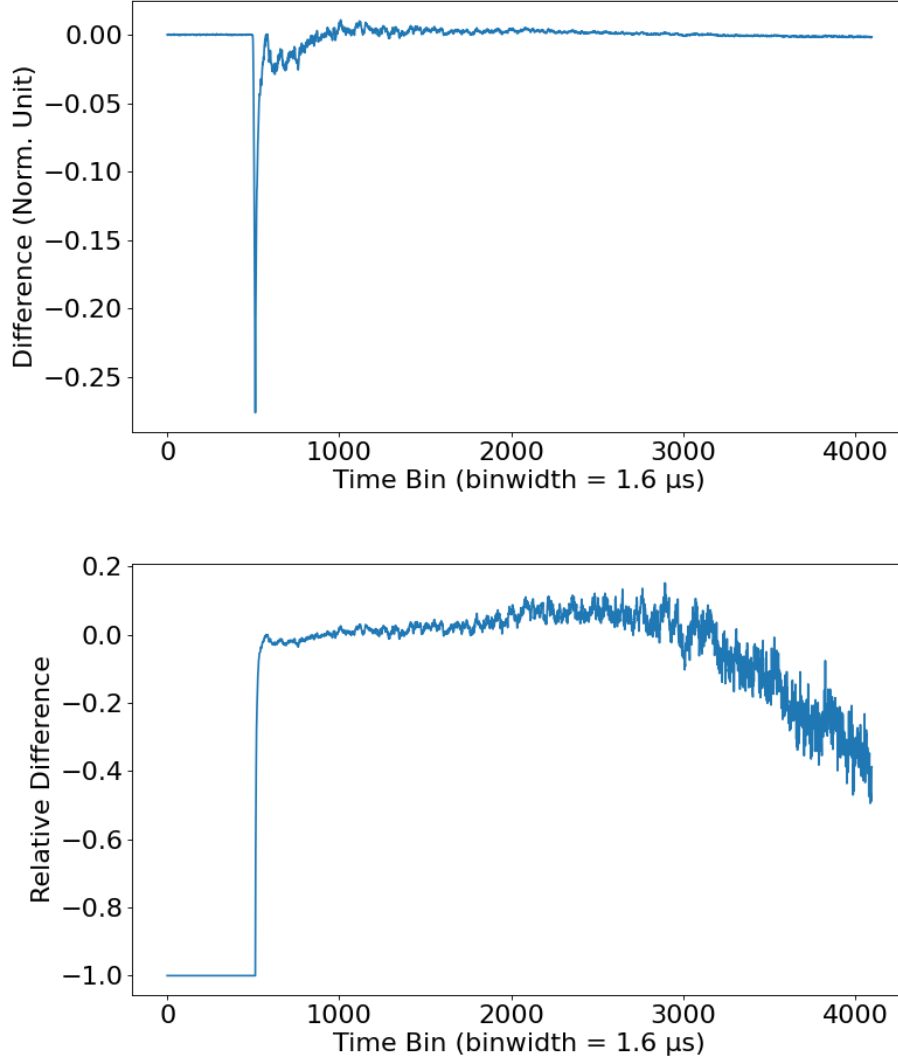


Figure 6.6: This figure presents two versions of differences between the scaled simulated total pulse and the Average Template from Figure 6.5. We show it to quantitatively illustrate the differences bin-by-bin (i.e. as a function of time). The top plot shows the absolute differences, calculated as the simulated total pulse minus the Average Template, where notable deviations are observed in  $500 < \text{bins} < 1000$  ( $800 < \text{time} < 1600 \mu\text{s}$ ). The bottom plot depicts the relative difference, calculated as the absolute difference divided by the Average Template, which reveals small but systematic variations in bins  $> 2000$  (time  $> 3200 \mu\text{s}$ ).

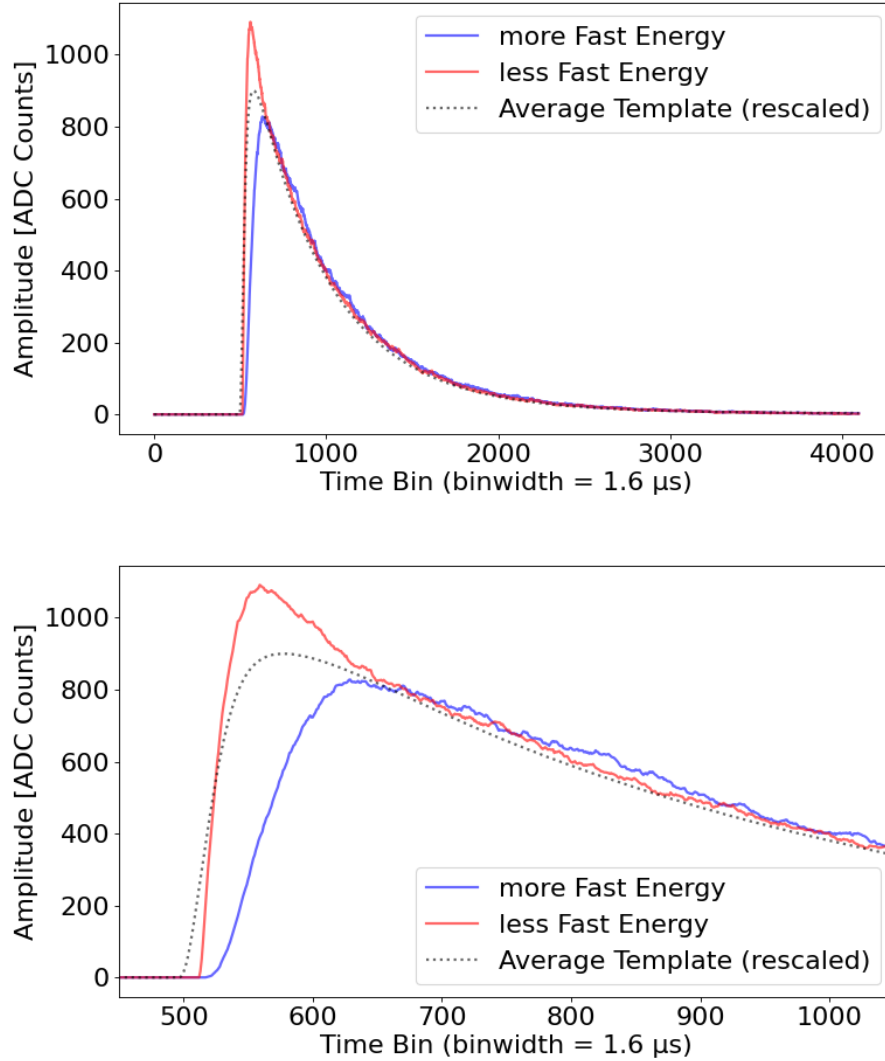


Figure 6.7: This figure shows the shapes of two individual pulses from a randomly selected well-measured event in simulation. We show it to visualize the similarity and difference in their shape characteristics in different time windows. For reference, we have added the shape of the Average Template, scaled to have a maximum that is the average of the two individual pulses for simplicity. As expected from Figure 3.15, the pulse with a greater amount of Fast Energy exhibits a sharper rise than the one with less Fast Energy, while both share a similar falling region due to Slow Energy being evenly collected by the channels.

the energy distribution we are reasonably well set up to have an apples-to-apples comparison of well-measured events. When we have confidence in the simulation the fraction of the events which are well-measured can be used in full analyses to estimate the dark matter cross section if there is an observation, or set reliable limits in the case of a non-observation. We also note that there is good agreement between the shape of the total pulse from simulations and real data which provides a good springboard for more detailed pulse-shape studies of individual channels which are expected to exhibit position-dependent response.

In the next chapter, we switch to using the EPot\_hits sample to delve into a quantitative study of phonon collection as a function of time and position, which assists with our thinking as we break our pulses into fast and slow components. Subsequently, in Chapters 8 - 10, we present a series of pulse-shape-based studies, examining variations across channels and applying these insights to identify poorly-measured events, estimate interaction positions, perform relative calibration, and investigate potential issues in the data and simulations.

## 7. MODELING THE PHONON ENERGY COLLECTION OVER POSITION AND TIME

In the previous chapter, our first comparison of simulated data to expectations showed qualitative agreement, covering the collected total phonon energy and the collection efficiency, the fiducial and non-fiducial regions, and the shapes of total and individual pulses. In this chapter, we move beyond the description in Section 3.3.1 to a more granular level by examining the arrival times and energies of individual phonons absorbed by the individual sensors as a function of position and time to gain a better understanding which microphysical processes produce the fast and slow components of the pulse shapes. In particular we are looking to describe the distributions of the fast and slow components of the phonon collection on a channel-by-channel basis with just a few parameters with an eye towards a more sophisticated and quantitative description of the expectations that go beyond the simple two-circle model shown in Figure 3.13. As we will, Fast and Slow Energy can usefully be separated at  $100\ \mu\text{s}$  after the energy deposit, and can be spacially-modeled as a Gaussian-like profile surrounding the interaction position and a uniform distribution, respectively.

In Section 7.1, we provide an overview of the phonon energy collection as a function of time and position by individual phonon sensors (QETs) in simulation. In Section 7.2, we present a more quantitative study of the phonon absorption position as a function of time, based on which we separate between Fast and Slow Energy. In Section 7.3, we describe the parameterized model of the Fast and Slow Energy distributions.

### 7.1 Phonon Energy Collection Over Time and Position

In this section, we describe phonon energy collection as a function of time and position by individual phonon sensors (QETs) in simulation. We use the EPot\_hits sample that simulates a single electron recoil interaction event at the center of the detector and records the time, energy and position information of each phonon absorption, as described in Section 5.2. We note that the distributions in this chapter represent only the phonon energy collection process and does not include the electrothermal response of the phonon sensors described in Section 3.3.2, which

ultimately shapes the final readout signal. In the first paragraph, we present the total phonon energy collection as a function of time, which exhibits a rapid rise followed by a slow falling part. In the second paragraph, we describe the positions where phonons are absorbed by the sensors at several time points, which provides insights for the separation between Fast and Slow Energy.

When considering the full set of QETs, the total phonon energy collection as a function of time quickly rises after the energy deposit, and then gradually decreases. As shown in top subfigure of Figure 7.1, the rising edge corresponds to the absorption of the subset of the phonons that arrive shortly after generation, as illustrated Figures 3.7 and 3.12. The remaining phonons undergo varying numbers of scatterings in the germanium and reflections off the detector edges before absorption, as described in Section 3.3.1; the gradual depletion of phonons within the detector results in the falling portion of the absorption curve. A plot of the cumulative phonon energy collection over time is shown in bottom subfigure of Figure 7.1.

The absorption of phonons by individual sensors is also a function of the QET position, varying over time from sensor to sensor, as illustrated in Figure 7.2. At the earliest times ( $< 5 \mu\text{s}$ ), the phonon absorption positions form a small disk-like region right above the interaction position that is at the detector's center in this case. As time progresses, we see that the distribution spreads across the full detector surface due to phonon scattering and bouncing behavior inside the detector. This spatial evolution supports a more refined understanding of Fast and Slow Energy, advancing beyond the simplified two-circle model previously introduced in Figure 3.13. A quantitative analysis will be presented in the next two sections, where we will show that we can usefully separate the two components at the  $100 \mu\text{s}$  time point, and model them as a position-dependent, Gaussian-like distribution and a uniform distribution, respectively.

Having overviewed the total phonon energy collection as a function of time and position, along with a simple qualitative description, in the next section we discuss the phonon absorption position along the radial direction over time, which allows us to make quantitative separations between the Fast and Slow Energy and provides the basis for modeling their spatial distributions.

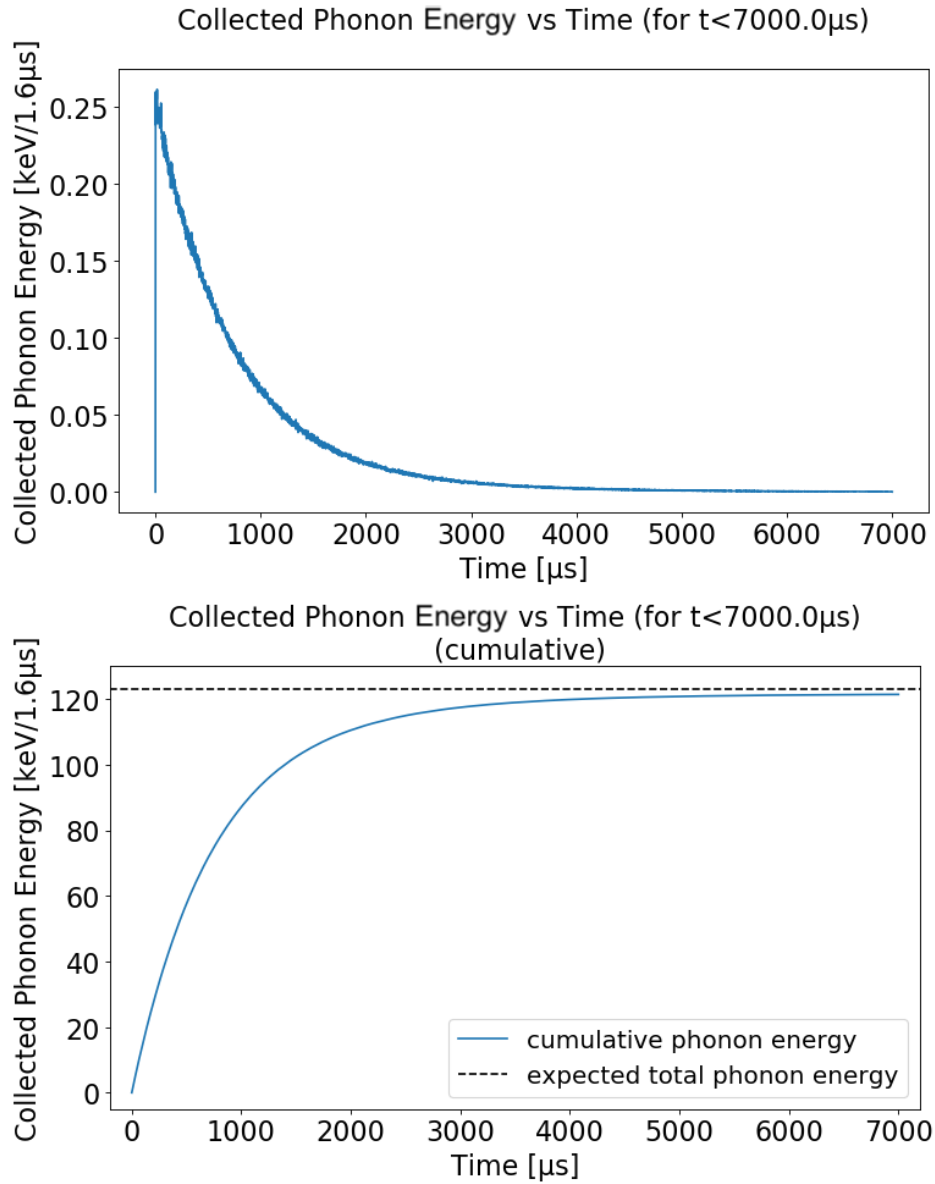


Figure 7.1: This figure shows two versions of the total phonon energy collection over time for the EPot\_hit sample. We show it to help indicate the fast and slow components of the phonon collection, which separates between phonons that are absorbed by the sensors at earlier time, and those that bounce numerous times before being collected. The top plot shows the amount of phonon energy collected in 1.6  $\mu\text{s}$  intervals, while the bottom plot displays the cumulative collection. Phonon energy is collected rapidly at first, then gradually slows down until the full amount is collected.

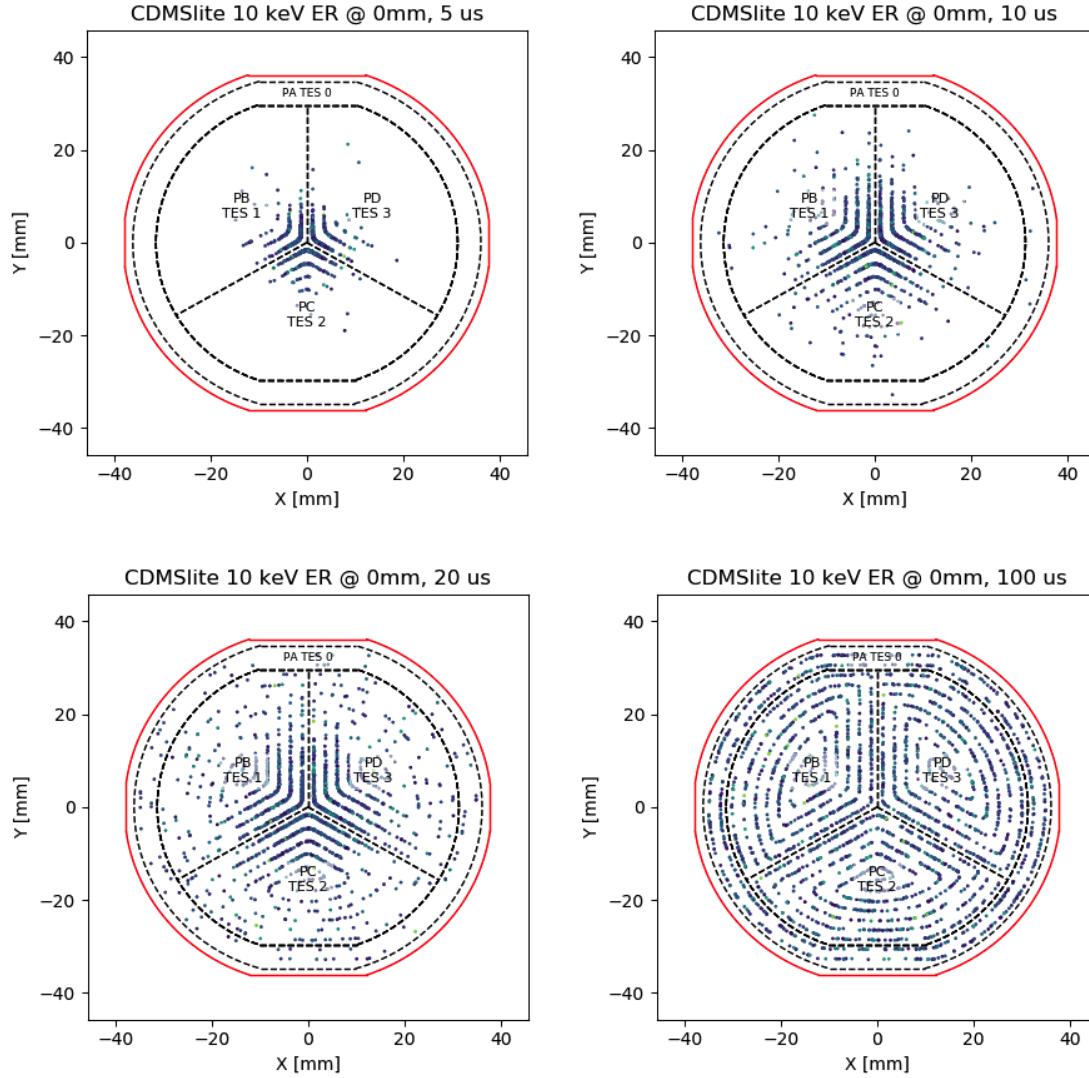


Figure 7.2: This figure shows the cumulative distributions of phonon absorption positions in QETs at four different times from the EPot\_hit simulation sample where the original interaction energy is deposited at the center of the detector. We show it to illustrate how the phonon absorption positions evolve over time, revealing that phonons can be separated into the fast and slow components. Initially, phonons travel toward the detector surfaces as shown in Figure 3.7 and then scatter and bounce within the detector until they are eventually absorbed by sensors. Upon absorption, the energy, time and positions are recorded. At early times, the phonons concentrate near the interaction position and get absorbed only by the nearby sensors (top left). As phonons scatter or bounce off the detector's edges, they gradually spread out and are absorbed by various sensors, eventually reaching a state of uniform distribution. Figure courtesy of Mike Kelsey.

## 7.2 Phonon Absorption Across Radial Positions Over Time

In this section, we take the next steps towards categorizing and parameterizing the description of the phonon absorption position as a function of time. This will be done in a couple of steps: identifying a set of sensors that allow for a clean parameterization as a function of radius, and then identifying a time when that parameterization changes. As shown in Figure 7.2, since absorption only occurs at fixed locations where phonon sensors are attached, we take advantage of the fact that these sensors both have partial symmetry around the origin and a few continuously located along the radial direction at the channel edges. Using data from this subset of sensors provides a basis for us to identify a reasonable separation time between the fast and slow phonons. In the first paragraph, we describe the selection of the region where the phonon sensors are continuously located along the radial direction. In the second paragraph, we describe how the phonon absorption changes over time. In the third paragraph, we discuss how we distinguish between the fast and slow phonons.

We use a spatial constraint to select the set of phonon sensors along the radial direction for use in our position and time study. The phonon sensors are mounted on the detector surfaces, with the layout shown in Figures 2.2 and 2.3a, and readily inferred from Figure 7.2 as the points where phonons are absorbed. In the boundary regions between the three inner channels (PB, PC, and PD), the sensors form a mostly-continuous radial configuration. We select the region between PB and PD, applying a spatial constraint of  $|X| < 2 \text{ mm}$  and  $Y > 0 \text{ mm}$ , as illustrated in Figure 7.3.

The distribution of phonon absorption positions in the selected sensor region as a function of time is shown in top subfigure of Figure 7.4 and allows for quantitative modeling. The weighted average (mean) and root mean square (RMS) as a function of time is shown in bottom subfigure of Figure 7.4. Both the mean and RMS values increase over time and eventually asymptote indicating a uniform distribution, as shown in Figure 7.5. Fitting to a simple asymptotic function,

$$f(t) = \frac{At^2}{t^2 + B} + 1, \quad (7.1)$$

where  $t$  is the time,  $A$  represents the asymptotic maximum,  $B$  is a rate coefficient, and the constant 1



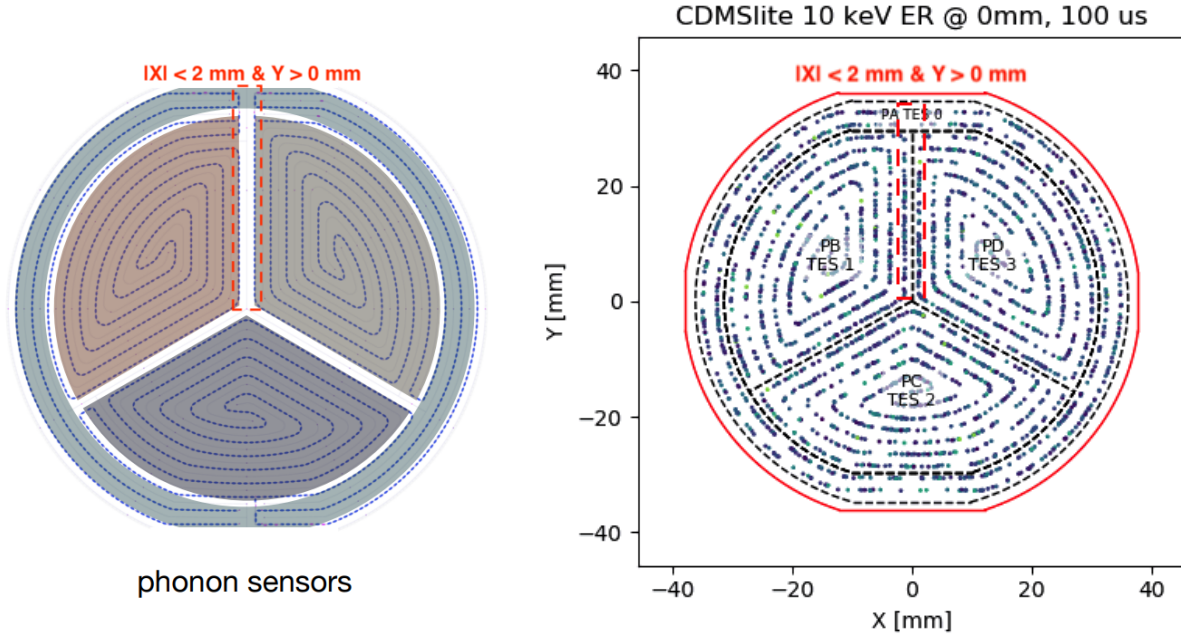


Figure 7.3: This figure highlights the selected region, indicated with the red-dashed box along the y-axis, used for studying the distribution of phonon absorption positions over time along the radial direction, based on Figures 2.3a and 7.2. We show this region because it contains a mostly-uniform set of phonon sensor locations along the radial direction, enabling a detailed analysis of phonon absorption position distributions evolving over time.

represents a hypothetical offset in the functional form, we obtain the maxima 14.71 mm and 8.61 mm for the mean and RMS, respectively. These two trendlines provide a basis for distinguishing between the fast and slow phonons.

The absorption positions become nearly uniform at  $100 \mu\text{s}$ , which we use to define the boundary between the fast and slow phonons. Based on the asymptotic fits, both the mean and RMS exceed 90% of their respective maxima at this time, as shown in Figure 7.5. This indicates that the remaining phonons in the detector become nearly uniformly distributed at this point, which we characterize as slow phonons in Section 3.3.1. Thus, the phonons collected before  $100 \mu\text{s}$  are characterized as the fast phonons. Accordingly, Fast and Slow Energy is distinguished by this time point.

Having described the distributions of the phonon absorption positions along the radial direction changing over time and established  $100 \mu\text{s}$  as a reasonable boundary to separate between the fast

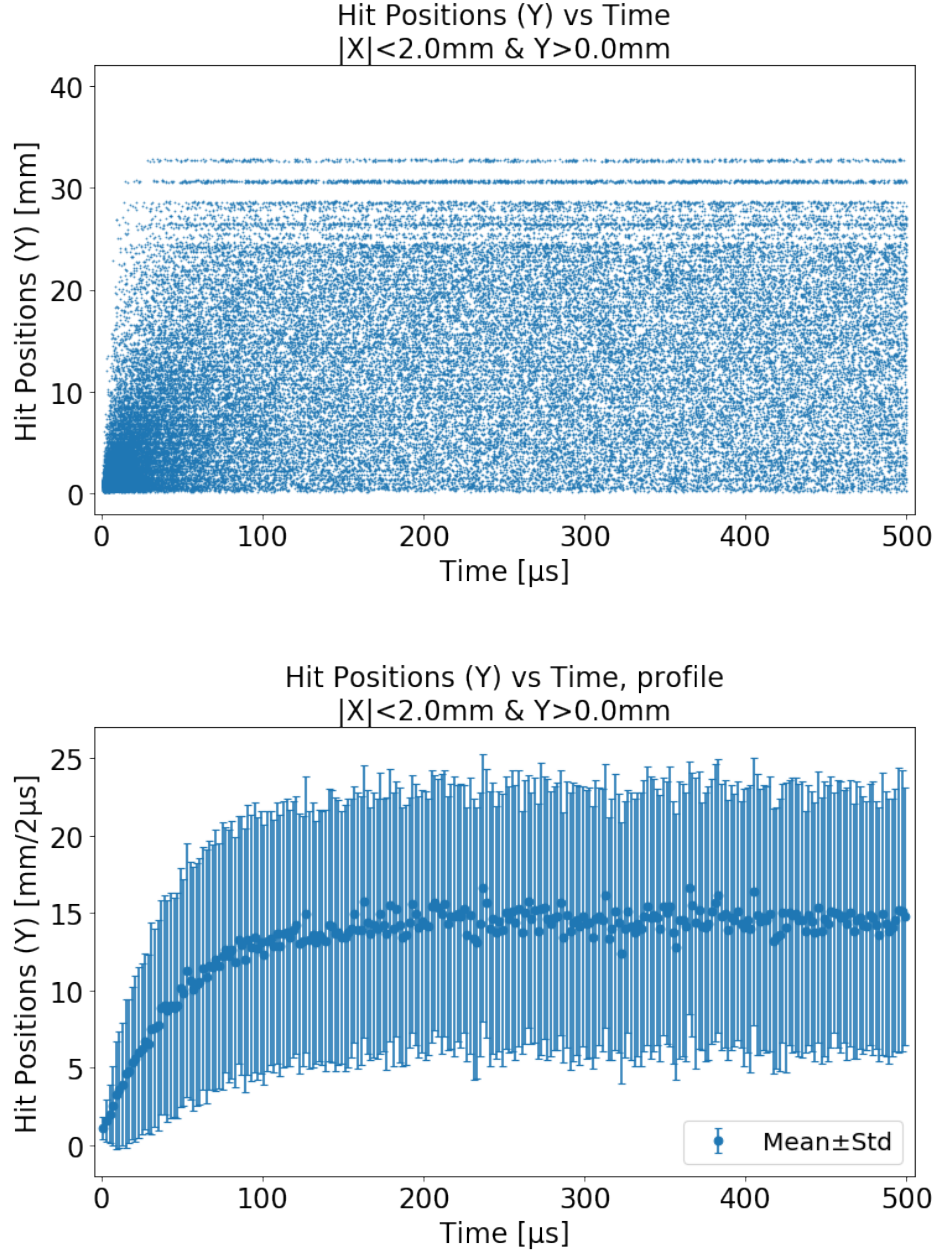


Figure 7.4: This figure shows two versions of how the phonon absorption positions in the radial direction evolves over the first 500  $\mu\text{s}$  from the EPot\_hit sample. We show it to illustrate the very different responses at early and late times. Only absorption positions recorded by the sensors in the selected region, shown in Figure 7.3, are included. The top plot shows the position and time for each phonon absorption, while the bottom plot displays the binned data, the average (mean) and the standard deviation (RMS) for each 2  $\mu\text{s}$  interval. It illustrates that the positions spread out within approximately 100  $\mu\text{s}$  and then stabilize, a behavior that will be quantitatively analyzed in Figure 7.5.

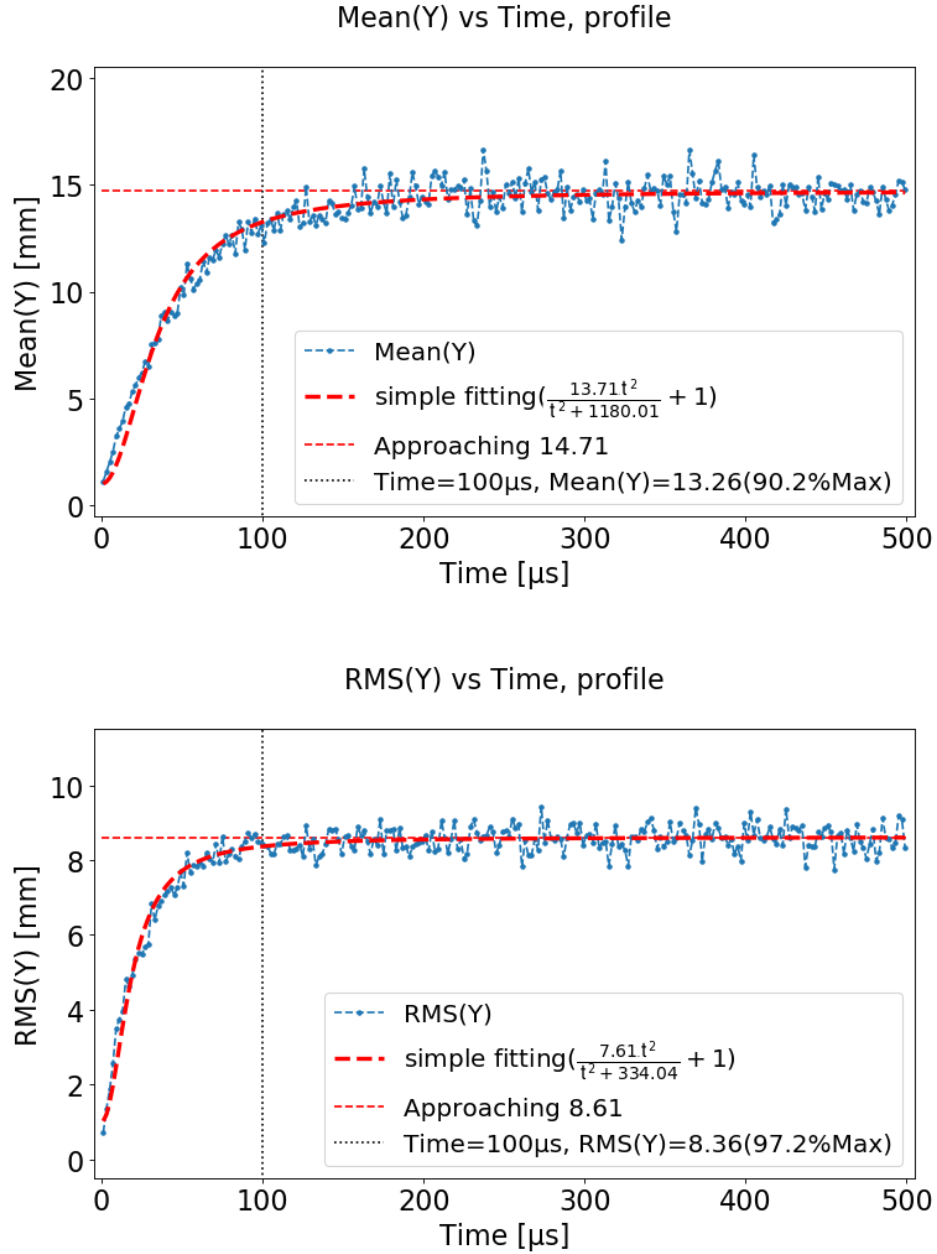


Figure 7.5: This figure shows how the mean and RMS values from Figure 7.4 evolve over time along with a simple asymptotic fit for each. We show it to further illustrate the results quantitatively and set the criteria for separating the fast and slow phonons. The top plot shows the mean value as a function of time, and the bottom plot shows the RMS value. Both reach over 90% of their asymptotic values at 100  $\mu\text{s}$ , which is selected as the boundary to separate the two components.

and slow phonons, we proceed in the next section to develop a model that quantitatively describes the phonon energy collection associated with each component (Fast and Slow Energy), focusing on the spatial distribution of the fast component.

### **7.3 Modeling the Spatial Distribution of Phonon Energy with a Fast and Slow Component**

In this section, we discuss the models developed to describe the spatial distribution of the collected phonon energy corresponding to the times before and after 100  $\mu$ s, Fast and Slow Energy. As we will see, we will be able to go beyond the simple two-circle description shown in Figure 3.13. The better description will be to model Fast Energy as a Gaussian-like distribution centered on the projection of the interaction position on the surface, and Slow Energy as a uniform distribution. Building the models involves a number of steps. In the first paragraph, we describe the first step where, for simplicity, we construct the spatial distributions along a whole diameter for the selected portions of Fast and Slow Energy, by mirroring the distribution along the radial direction. In the second paragraph, we fit the constructed distribution of Fast Energy along the whole diameter with a generalized Gaussian function. In the third paragraph we quantify the fraction of the Fast and Slow Energy.

The first step is to construct the spatial distributions along a diametrical slice for the selected portions of Fast and Slow Energy for simplicity of fitting. Using 100  $\mu$ s as the boundary between them, we plot the total energy density as a function of  $y$  which we assume is a good approximation for all angles around this point since the interaction occurs at the origin, as shown in Figure 7.3. A symmetric version along the full diameter is then obtained by mirroring the distribution about the detector center, as shown in Figure 7.6. We observe that the Fast Energy distribution resembles a Gaussian-like profile, while the Slow Energy distribution appears nearly uniform.

Next we fit the Fast Energy distribution with a generalized Gaussian function, assuming the distribution has mirror symmetry around the interaction point. Given that the distribution can be thought of as a sum of Gaussian's with varying standard deviations, we can model it with the

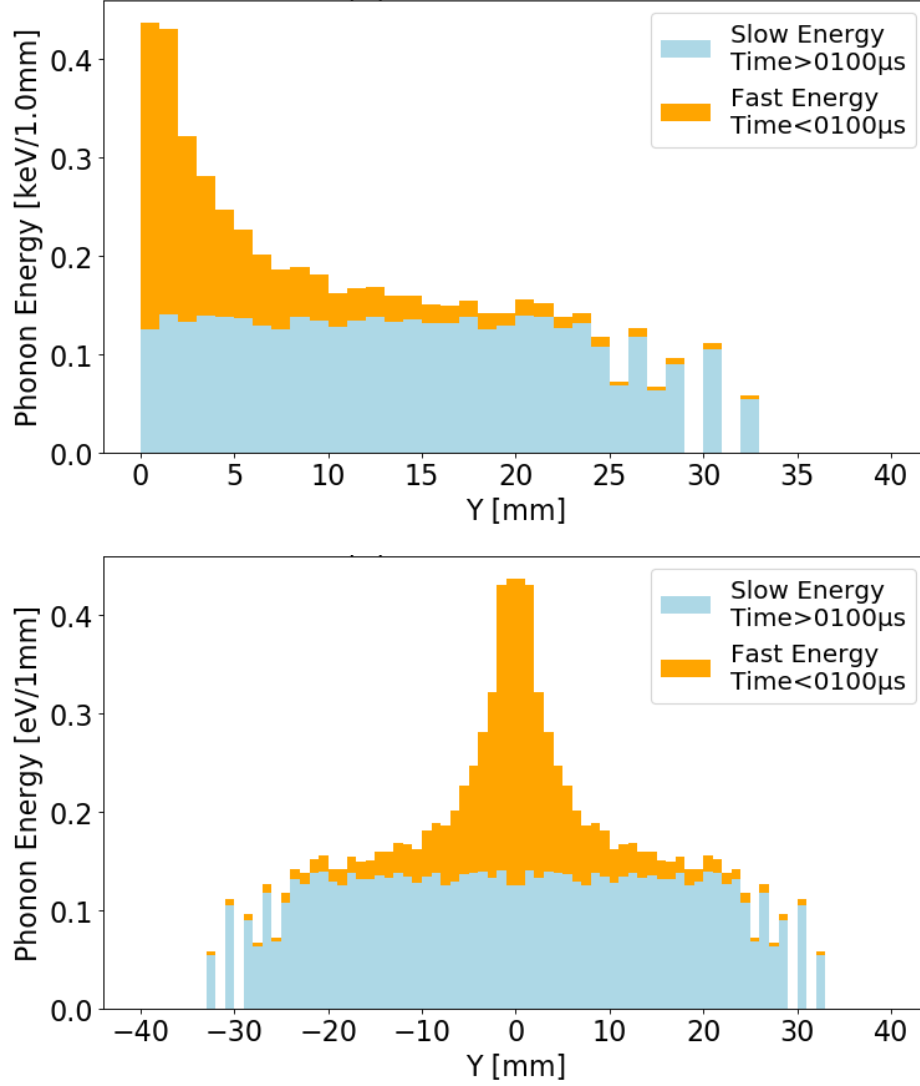


Figure 7.6: This figure shows the distributions of collected phonon energy as phonons are absorbed by the sensors located along the radial direction, defined in Figure 7.3, with Fast (orange) and Slow (blue) Energy separated by a  $100 \mu\text{s}$  time threshold. We show it to illustrate the distinct spatial profiles of the Fast and Slow Energy distributions. The top plot shows the original data. The bottom plot presents a mirrored version to approximate the distribution along the whole diameter for visualization and fitting purposes: Fast Energy exhibits a Gaussian-like shape, whereas Slow Energy is nearly uniformly distributed.

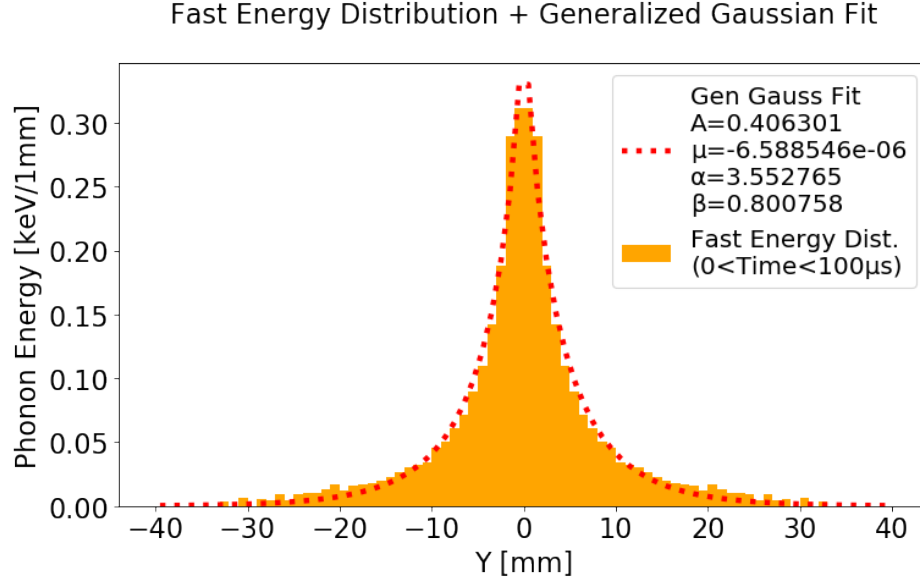


Figure 7.7: This figure shows the constructed distribution of Fast Energy along the whole diameter shown in Figure 7.6 along with the best fit from the generalized Gaussian model. We show it to illustrate that the Fast Energy distribution can be well-modeled using a generalized Gaussian function,  $Ae^{-\left(\frac{y-\mu}{\alpha}\right)^\beta}$ , with the parameter values provided in the legend. Similar results for different interaction positions are shown in Appendix C for completeness.

functional form

$$f(y) = A \exp \left( - \left( \frac{|y - \mu|}{\alpha} \right)^\beta \right), \quad (7.2)$$

where  $A$  is the amplitude,  $\mu$  is the center (the projection of the interaction position on the detector surface),  $\alpha$  is the scale parameter, and  $\beta$  is the shape parameter. We fit the Fast Energy distribution along the full diameter using this function and obtain the parameters  $A = 0.4$ ,  $\mu = 0$ ,  $\alpha = 3.5$ , and  $\beta = 0.8$ , as shown in Figure 7.7; using the standard estimates of the variance for a generalized Gaussian we find  $\sigma = 7.73$  mm. We note that we also studied the Fast Energy distribution for interactions occurring at different radial positions, as shown in Appendix C; qualitatively the results are similar, but reflections of Fast Energy at the sidewalls make a quantitative description more complex.

Finally, we quantify the fraction of Fast and Slow Energy to complete our quantitative model. For a 10 keV electron recoil in the simulation, the total phonon energy is 123.24 keV, as described in

Section 3.2.1. Fast Energy accounts for 14.66 keV (12.06%), as extracted from the data illustrated in Figure 7.1. The remaining 108.58 keV (87.94%) is described as Slow Energy modeled as a uniform spatial distribution. With these pieces, and the assumption of symmetry around the interaction, the functional form provides the results in Figure 7.8 as a heat map of the total phonon energy as a function of position.

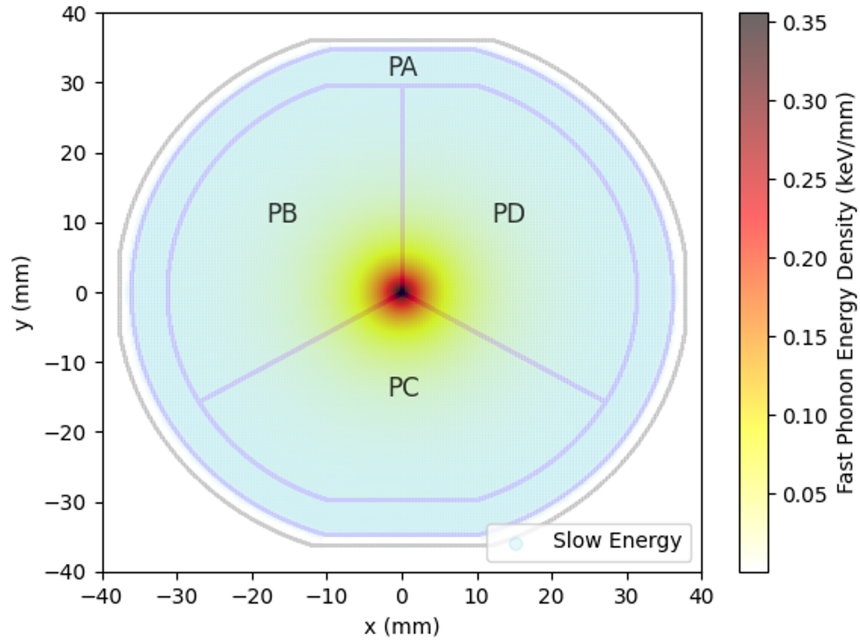


Figure 7.8: This figure shows an idealized heat map of the total collected phonon energy as a function of position based on the Gaussian+flat model for Fast and Slow Energy, where we have assumed radial symmetry around the interaction position at the center. We show it to compare to the simple two-circle model shown in Figure 3.13. Figure courtesy of Dylan Monteiro.

Having described a Gaussian+flat model for the spatial distribution of the two components of the total phonon energy, Fast and Slow Energy, we now have an intuitive sense of how to predict the distribution in each of the four channels. In the next chapter we will come back to the well- and poorly-measured events as discussed in Section 6.2, focusing on methods to reject the poorly-measured events and to estimate the interaction positions using the simulated data. In the

chapters after that, we will present a set of comparisons between simulated and real pulses, along with calibration of the pulse scaling and discussing the physics underlying the discrepancies.



## 8. REJECTING POORLY-MEASURED EVENTS AND ESTIMATING THE INTERACTION POSITIONS OF WELL-MEASURED EVENTS (SIMULATION ONLY)

In this chapter, we describe a set of methods we have developed to both reject poorly-measured events and estimate the interaction positions of well-measured events using what we have learned from the simulations about the early portion of individual pulses. As described in Section 4.2, the search for dark matter requires removing as many poorly-measured events as possible and there is value in having accurate position measurements for well-measured events to compare with the expectations of the fiducial regions described in Section 6.2. While previous methods have been developed and used [14], their use was only partially justified as there was no method to confirm their veracity. The methods presented here, based on the simulated pulses in the EPot sample described in Section 5.2, are designed to be simple and only use quantities that are also available in the real data. As we will see, these approaches are suggestive for future analysis as they are expected to reject 99% of the poorly-measured events and estimate the interaction positions with accuracy up to 0.5 mm for radial position and  $1.0^\circ$  for angular position. For convenience, the radial position, the distance between the interaction position and the detector center, is denoted as  $R$ ; the angular position, the angular difference between the interaction position and the center of the lead channel, is denoted as  $|\Delta\Phi|$ . If we can provide evidence that our simulation is reliable this would be a major step forward.

Previous chapters suggest that both the collection efficiency and the early portion of individual pulses are correlated with the interaction position in the detector, which may provide the key to reject poorly measured events and estimate the interaction positions. As previously shown in Figures 6.3 and 6.4, poorly-measured events in the simulation samples predominantly occur at large radial positions, with a smaller fraction near the top or bottom of the detector. Given that the results of Figure 7.8 indicate that the location of the earliest and most energetic phonons are absorbed directly above the interaction position this suggests focusing on and comparing the early portion of each of the individual pulses. For the reasons we will describe, the amplitudes of the pulses

at the times shown in Figure 8.1 are selected as our position-dependent quantities to describe the early portion of the pulse shape, and closely follow the expected position-dependent amount of Fast Energy collected by each channel as shown in Figure 8.2.

In Section 8.1, we describe the motivation and construction of the two sets of pulse shape quantities. In Section 8.2, we describe a number of methods to reject poorly-measured events, and evaluate their performance. In Section 8.3, we describe the methods to estimate the interaction position ( $R$  and  $|\Delta\Phi|$ ) for well-measured events, and evaluate their accuracies by comparing them to the truth values in simulation.

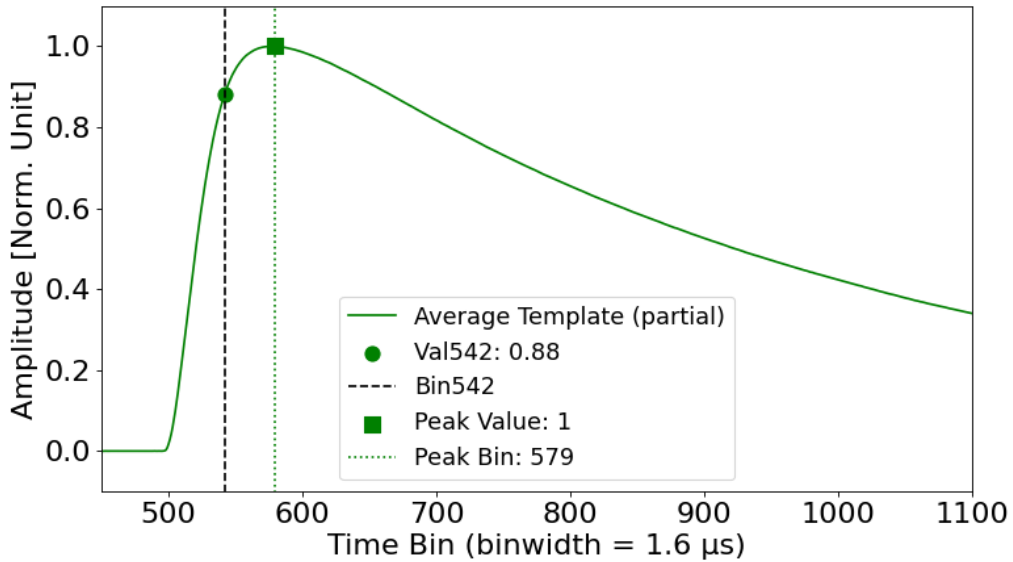
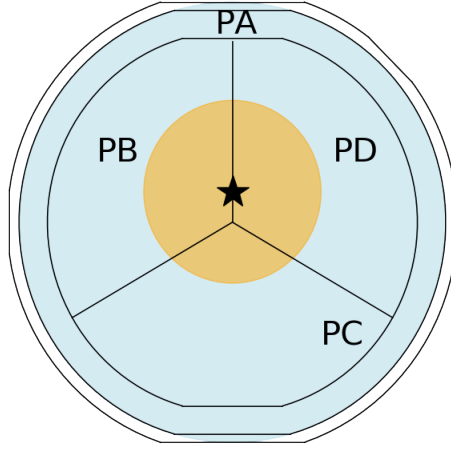
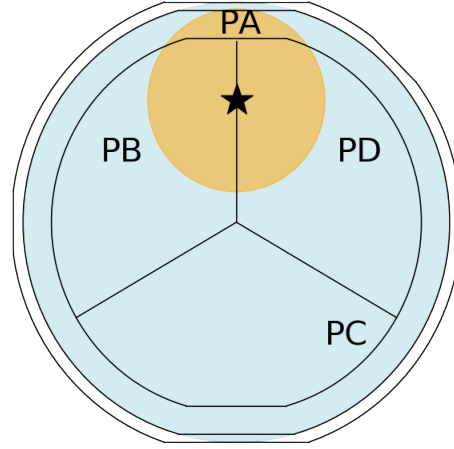


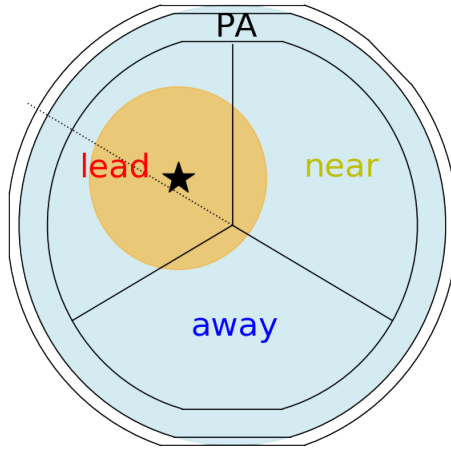
Figure 8.1: This figure shows the region of the Average Template that contains the peak of the pulse along with two identified points for use in our analysis. We show it to illustrate the three quantities used to characterize early portion of the pulse shape; the time bin at which the pulse reaches its maximum and its corresponding pulse value, *Peak Bin* and *Peak Value*, and the pulse value at the 542nd bin, *Val542*. The Average Template, constructed and scaled to a peak value of 1, has *Val542* of 0.88, *Peak Bin* of 579 and *Peak Value* of 1.



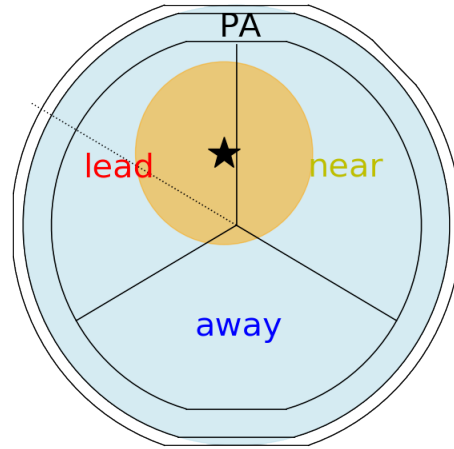
(a) Interaction at  $R = 5$  mm



(b) Interaction at  $R = 20$  mm



(c) Interaction at  $10^\circ$   
from the center of the lead channel



(d) Interaction at  $50^\circ$   
from the center of the lead channel

Figure 8.2: This figure shows four diagrams of the simplified two-circle model as previously shown in Figure 3.13 with stars indicating the hypothetical interaction positions. We show it to qualitatively illustrate how the amount of energy collected in a channel is a function of the interaction position. The top two diagrams show the case for an interaction that occurs at  $R = 5$  mm and  $R = 20$  mm (along the boundary between PB and PD), and the bottom two for  $|\Delta\Phi| = 10^\circ$  and  $|\Delta\Phi| = 50^\circ$  away from the center of the lead channel indicated as a dashed line.

## 8.1 Constructing Pulse Shape Quantities Correlated with the Interaction Positions

In this section, we describe the motivation and construction of two sets of quantities derived from the pulse shapes in events from the EPot sample. Since, as described in the previous chapter and shown in Figure 8.2, the amount of Fast Energy collected by a channel is a function of interaction positions, we focus on the early times and identify simple quantities that can be uniquely determined for individual pulses both in simulated and real data. As illustrated in Figure 8.1 using the Average Template, we use the time bin at which the pulse reaches its maximum and its corresponding pulse value, referred to as *Peak Bin* and *Peak Value*, and the pulse value at bin 542, denoted as *Val542*, for reasons discussed below. For each pulse we will include a subscript to indicate when we are considering pulses from either combined channels (such as ‘BCD’ which stands for combined PB, PC, and PD channels) or an individual channel (such as lead, near and away) using the notations shown in Figure 8.2. We start by only considering well-measured events to verify the usefulness of these quantities, and come back to their distributions in poorly-measured events to establish rejection criteria in Section 8.2. As we will show, these variables are also effective as estimating the interaction location for well-measured events. In the first paragraph, we quantify how the  $R$  of an interaction affects the amount of Fast Energy collected by the lead channel, which can be observed in its *Peak Bin*, referred to as  $PeakBin_{lead}$ . In the second paragraph, we describe how we use the correlation between  $PeakBin_{lead}$  and  $R$  to reject poorly-measured events. In the third paragraph, we motivate the use of *Val542*, as a powerful indicator of the amount of Fast Energy collected by the various channels, for use in both rejecting poorly-measured events and estimating interaction positions. In the fourth paragraph, we describe the variations of four *Val542* quantities ( $Val542_A$ ,  $Val542_{BCD}$ ,  $Val542_{lead}$  and  $Val542_{near}$ ) and how they are used to reject poorly-measured events and estimate interaction positions for well-measured events.

The amount of Fast Energy collected by the lead channel varies with  $R$ , which allows for the use of the variation of  $PeakBin_{lead}$  with  $R$  for our purposes. Following the simple two-circle model examples in Figures 8.2c and 8.2d, the channel with the largest overlap of the yellow circle (Fast Energy) gives that channel the most portion, which is why it is referred to as the lead channel. The

lead channel collects 1/3 of the yellow circle for events at  $R = 0$  mm, but more as  $R$  increases, albeit with variation from  $|\Delta\Phi|$ . With even larger  $R$  the circle starts to overlap significantly with the outer channel (PA), indicating less Fast Energy as well as later arrival in any of the inner channels. At the largest  $R$  values the circle approaches the sidewall and a part of it lies outside the detector. This unphysical prediction indicates a break down of the simple model which suggests that the processes that dominate start to change, including a larger fraction of the fast phonons interacting with the sidewall at early times which can affect things. Similarly, we expect that the reduced electric field at large  $R$  affects the production of the fast phonons. Accordingly, for the full range of  $R$ , we expect that, as we move away from  $R = 0$  mm, the value  $PeakBin_{lead}$  will quickly will get earlier for a few mm, then remain roughly constant with variations for a range of  $R$  where the interaction is well within the inner channels, and then rise again as it approaches the detector sidewall.

Moving from qualitative descriptions to the quantitative correlation between  $PeakBin_{lead}$  and  $R$  we show the results for the sample in Figure 8.3. The value of  $PeakBin_{lead}$  is about 560 for events with  $R < 2$  mm, and as expected decreases slightly and remains at around 542 on average for events occurring up to  $R < 25$  mm, and then rises to about 600 as  $R$  approaches the edge of the detector. The  $PeakBin_{lead}$  value of 542 in the bulk of the well-measured region motivates the use of  $Val542$  and illustrates that the  $R$ -dependent variation can be used to reject poorly-measured events that mostly occur at large  $R$ , with results shown in the next section.

A set of  $Val542$  variables are used for estimating interaction positions, motivated by the symmetry of the channel layout and the Fast Energy distribution. Since the circular region of the Fast Energy distribution needs to be somewhere, we take advantage of the angular symmetry of the channels around the origin to note that it must be split between the outer channel (PA) and the combined inner channels (PB+PC+PD) regardless of the angular position of the interaction. Said differently, the sharing of Fast Energy between these two sets of channels has the advantage of removing the angular dependence, but retaining the  $R$  dependence only. This makes  $Val542_A$  and  $Val542_{BCD}$  well-suited for both rejecting poorly-measured events and estimating  $R$  for well-measured events. Using similar arguments but with an emphasis on maximizing the variation as a function of angle,

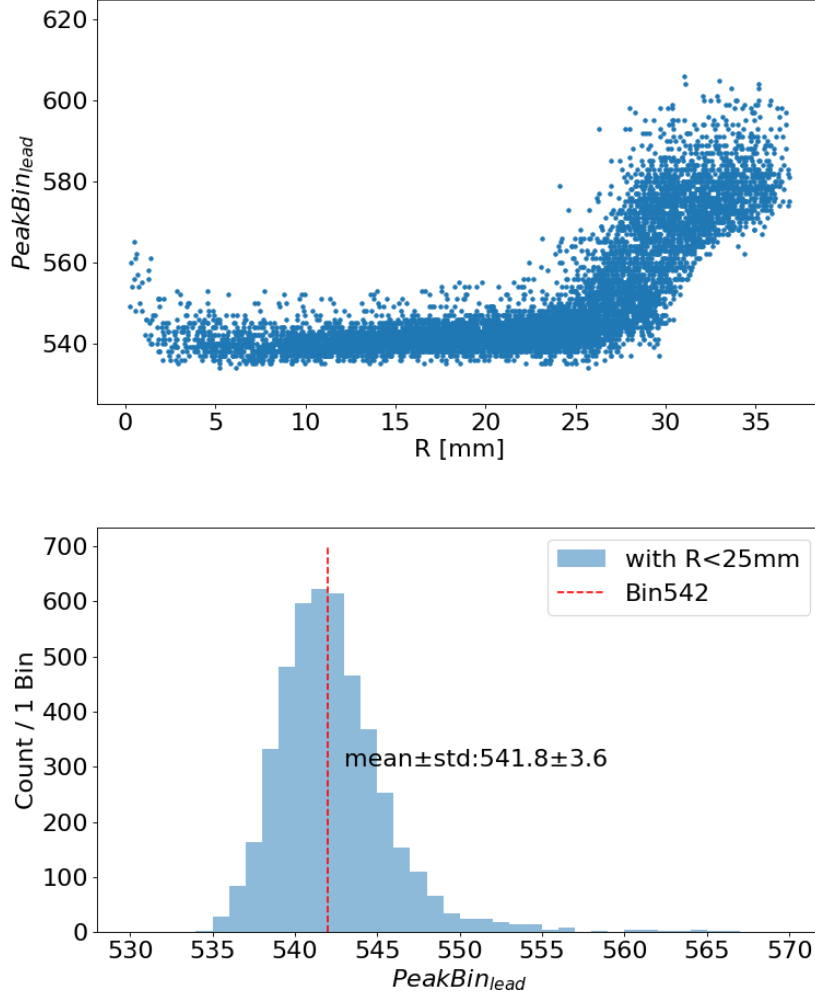


Figure 8.3: This figure shows two versions of the *Peak Bin* of the lead channel,  $PeakBin_{lead}$ , as a function of  $R$  for the well-measured events shown in Figure 6.4. We show it to illustrate the value of  $PeakBin_{lead}$  for use in the rejection of poorly-measured events. The top plot displays the range of values across all  $R$ , while the bottom plot provides a histogram focused on  $R < 25$  mm. The values of  $PeakBin_{lead}$  remain relatively constant for  $R < 25$  mm but increase significantly for  $R > 25$  mm, enabling  $PeakBin_{lead}$  to serve as a criterion for distinguishing between well- and poorly-measured events, which generally occur for  $R < 29$  mm and  $R > 29$  mm, respectively.

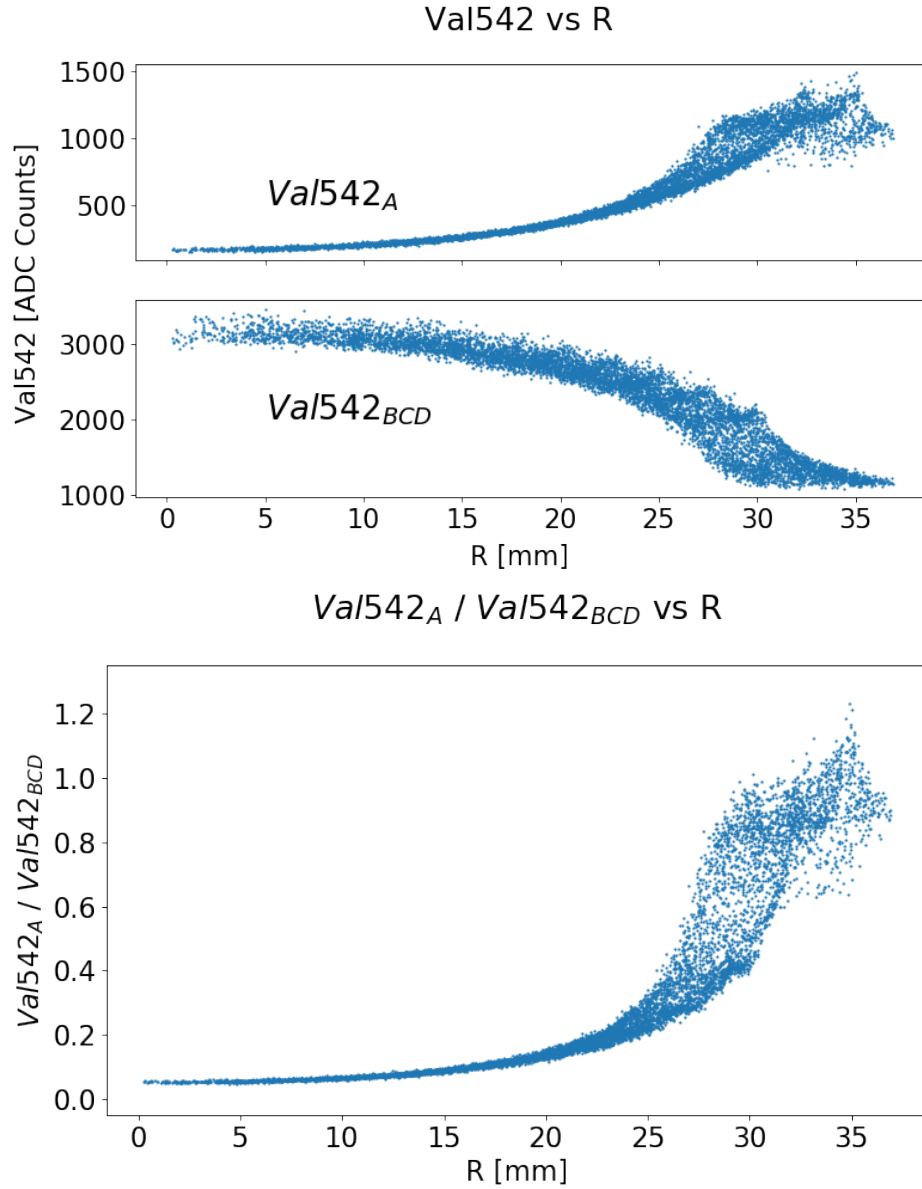


Figure 8.4: This figure shows the pulse value at bin 542 for the outer channel (PA) and the combined inner channels (PB+PC+PD), denoted as  $Val542_A$  and  $Val542_{BCD}$ , as a function  $R$  for well-measured events in the EPot sample. We show it to illustrate how these values vary with  $R$ , enabling both the rejection of poorly-measured events and the estimation of  $R$ . As  $R$  increases,  $Val542_A$  increases while  $Val542_{BCD}$  decreases. The ratio  $Val542_A/Val542_{BCD}$  is even more sensitive to  $R$ .

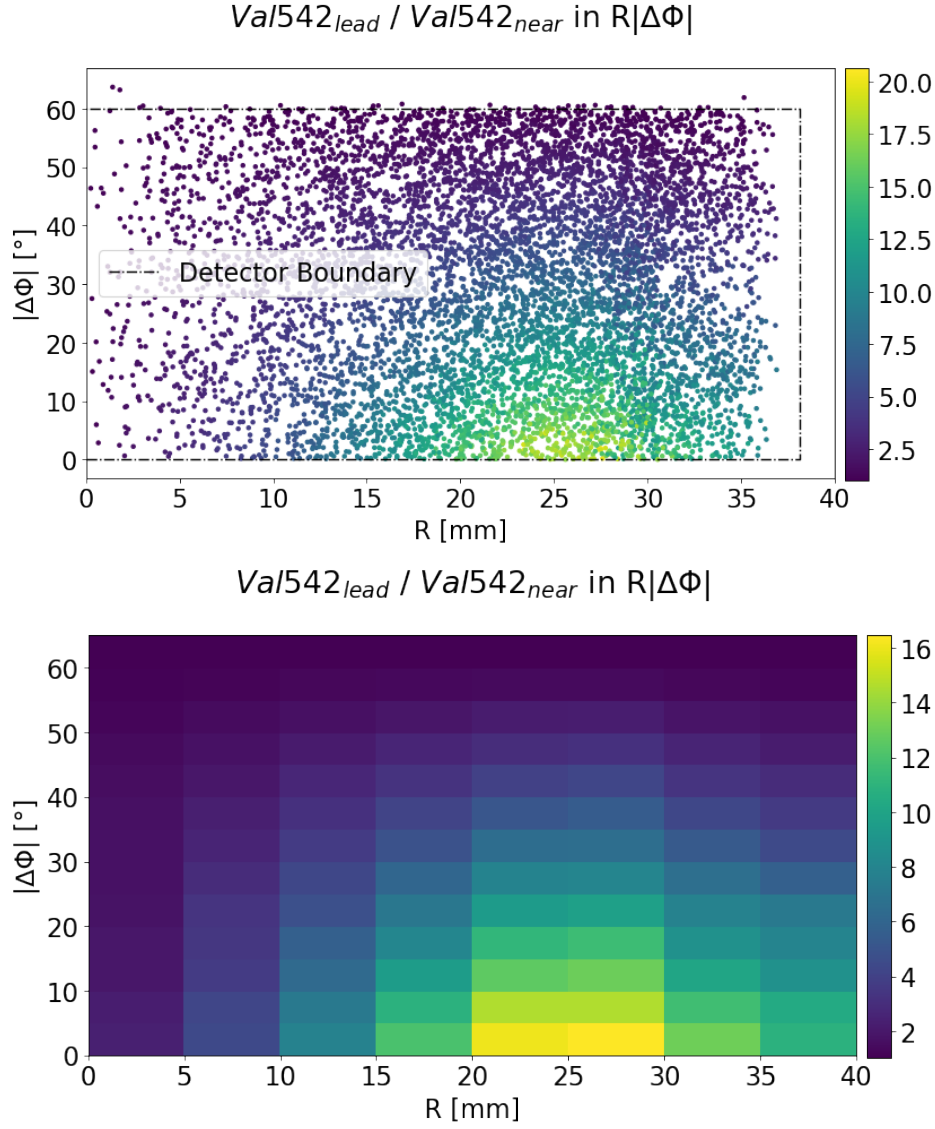


Figure 8.5: This figure shows two versions of the ratio  $Val542_{lead}/Val542_{near}$  in the  $R|\Delta\Phi|$  plane for the same set of events used in Figure 8.4. We show it to illustrate how this ratio depends on both  $R$  and  $|\Delta\Phi|$ . The top plot is a scatter plot in which each point represents an event, color coded by its value of  $Val542_{lead}/Val542_{near}$ . The bottom is a profile plot showing the average value of  $Val542_{lead}/Val542_{near}$  for events within each cell, with cell sizes of  $R = 5$  mm and  $|\Delta\Phi| = 10^\circ$ . Both plots reveal that the ratio maximizes near  $R = 25$  mm and  $|\Delta\Phi| = 0^\circ$ , decreasing as the distance from this point increases. We note that the points outside the detector boundary in the top plot arise from cases where the lead and near channels are misidentified due to fluctuations.



we note that since the Fast Energy sharing between the lead and near channels changes with both  $R$  and  $|\Delta\Phi|$ , indicating that a combination of the  $Val542_{lead}$  and  $Val542_{near}$  quantities can be useful to estimate  $|\Delta\Phi|$ .

Again, moving from qualitative descriptions to the quantitative correlations, Figure 8.4 shows  $Val542_A$  and  $Val542_{BCD}$ , both separately and combined as a ratio, as a function of  $R$ . The ratio  $Val542_A/Val542_{BCD}$ , which exhibits a stronger dependence on  $R$  than either quantity alone, is used to estimate  $R$ . Figure 8.5 shows the ratio  $Val542_{lead}/Val542_{near}$  as a function of  $R$  and  $|\Delta\Phi|$ . With an estimated  $R$ , this ratio provides a means to estimate  $|\Delta\Phi|$ . The use of these variables will be presented in detail in the next two sections, respectively.

With our description of the useful quantities that can be uniquely and easily derived from the pulse shapes, and how and why they vary as a function of position for well-measured events complete, we next show how well these variables do at rejecting poorly-measured events. With the ability to select well-measured events in hand, in Section 8.3 we will proceed to use the quantities to estimate the interaction position for well-measured events.

## 8.2 Rejecting Poorly-Measured Events

In this section, we describe the methods to reject poorly-measured events using  $PeakBin_{lead}$  and  $Val542_A/Val542_{BCD}$ . By comparing the distributions of these quantities for both well- and poorly-measured events, we establish criteria to separate and reject the poorly-measured events. As we will see, with our final selection we are able to reject 99% of the poorly-measured events while retaining most of the well-measured events.

The value of both  $PeakBin_{lead}$  and  $Val542_A/Val542_{BCD}$  are shown in Figures 8.6 and 8.7 respectively for the full sample of events using the same color coding as in Figure 6.4. Since most poorly-measured events have  $PeakBin_{lead}$  later than 562, with a few earlier than 534, a simple application of these values as thresholds allows us to reject 98.8% of poorly-measured events while retaining 75.4% of the well-measured ones. Similarly, most poorly-measured events have  $Val542_A/Val542_{BCD}$  values greater than 0.37. Using this criterion alone allows us to reject 98.5% of poorly-measured events while keeping 67.5% of well-measured events. The correlation

between the two quantities is shown in Figure 8.8 and a set of joint criteria, summarized in Table 8.1, achieves a rejection rate of 99.0% for the poorly-measured events while retaining 77.8% of the well-measured events. We note that the bulk of the remaining poorly-measured events are from the top and bottom surfaces, for which there are no known quality methods to reject them.

With the methods developed to reject poorly-measured events described and their effectiveness presented, we move forward to describe our methods of estimating the interaction positions and evaluating their accuracy and resolution in the next section.

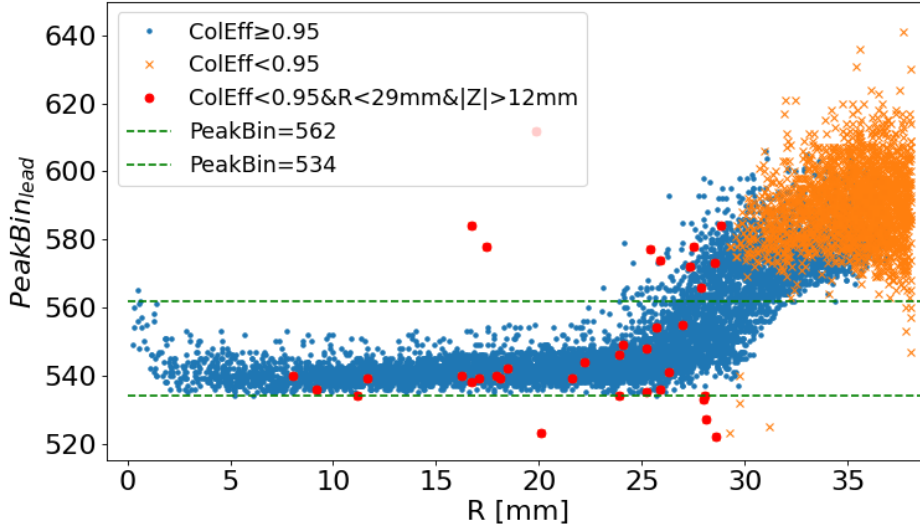


Figure 8.6: This figure is the same as the top plot in Figure 8.3 but includes poorly-measured events as well, where each is color-coded using the same color scheme as in Figure 6.4. We show it to illustrate the criteria for rejecting poorly-measured events using  $PeakBin_{lead}$ . Well- and poorly-measured events can be largely separated by the flat criterion of  $PeakBin_{lead} = 534$  and  $PeakBin_{lead} = 562$  (green dashed lines). Events between the two dashed lines are recognized as well-measured events and otherwise poorly-measured events. This criterion effectively rejects most poorly-measured events, though some well-measured events are also removed. The number of events for both are listed in Table 8.1.

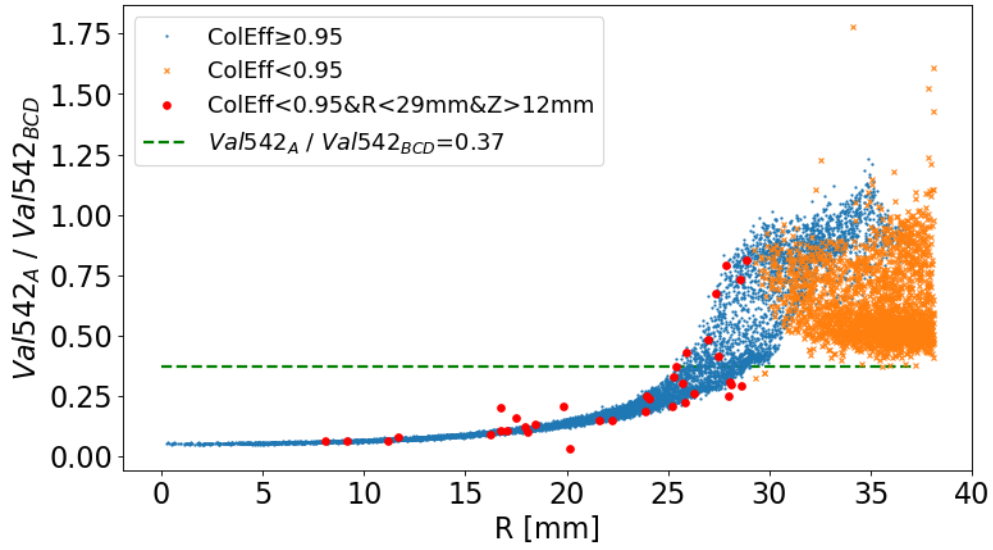


Figure 8.7: This figure shows the value of the ratio  $Val542_A/Val542_{BCD}$  as a function of  $R$  for the same events and color coding as in Figure 8.6. We show it to illustrate the criteria for rejecting poorly-measured events using this ratio. Well- and poorly-measured events can be largely separated by a flat criterion,  $Val542_A/Val542_{BCD} = 0.37$ . This criterion effectively rejects most poorly-measured events, though some well-measured events are also removed. The number of events for both are listed in Table 8.1.

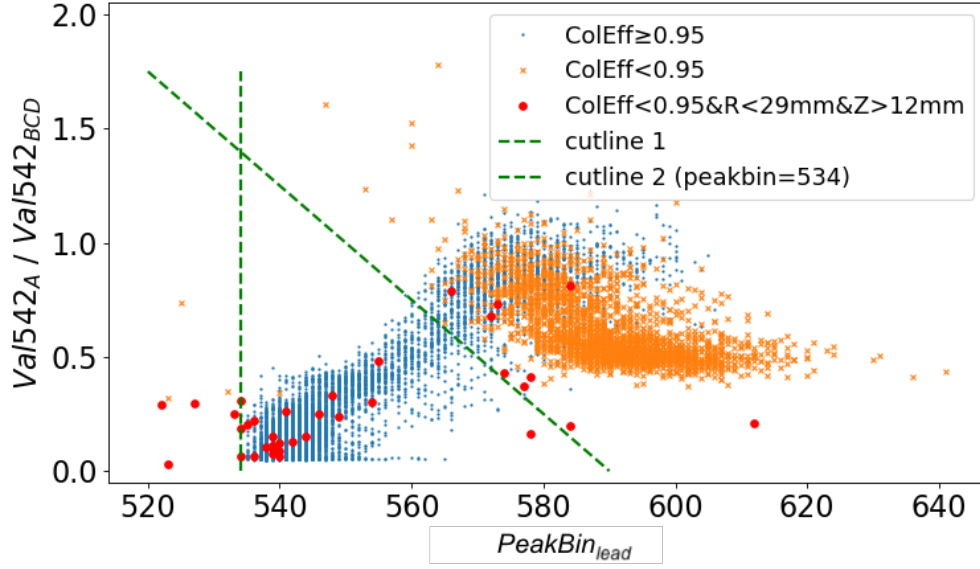


Figure 8.8: This figure shows the correlation between the measured quantities shown in Figures 8.6 and 8.7 with the same color coding. We show it to illustrate the criteria for rejecting poorly-measured events using a combination of both quantities. Well- and poorly-measured events can be largely separated by a joint criterion of  $Peak\ Bin = 534$  (green dashed cutline 2) and  $Val542_A / Val542_{BCD} + 0.025 \times PeakBin_{lead} = 14.75$  (green dashed cutline 1). Events under the two dashed lines are recognized as well-measured events and otherwise poorly-measured events. This criterion effectively rejects most poorly-measured events, though some well-measured events are also removed. The number of events for both are listed in Table 8.1.

Table 8.1: This table lists the three different sets of criteria for accepting and rejecting well- and poorly-measured events, as described and illustrated in Figures 8.6 - 8.8, and summarizes the number of accepted and rejected events from the EPot sample. As a reminder, well-measured events are defined as having a collection efficiency of  $\geq 0.95$  and poorly-measured events as having a collection efficiency of  $< 0.95$ , as shown in Figure 6.2, which is also given in the first row. Each criterion effectively rejects the majority of poorly-measured events while accepting different levels of well-measured events. Using a combination of  $Val542_A/Val542_{BCD}$  and  $PeakBin_{lead}$ , we achieve an excellent balance; high rejection of poorly-measured events with large retention of well-measured events.

Selection Criteria and Number of Accepted and Rejected Events

| Selection Criteria                                                                              | Pass<br>or<br>Fail | Well-Measured<br>(ColEff $\geq 0.95$ )<br>7860 events | Poorly-Measured<br>(ColEff $< 0.95$ )<br>2140 events |
|-------------------------------------------------------------------------------------------------|--------------------|-------------------------------------------------------|------------------------------------------------------|
| $534 \leq PeakBin_{lead} \leq 562$                                                              | Pass<br>Fail       | 5925 (75.4%)                                          | 2115 (98.8%)                                         |
| $Val542_A/Val542_{BCD} \leq 0.37$                                                               | Pass<br>Fail       | 5306 (67.5%)                                          | 2109 (98.5%)                                         |
| $(PeakBin_{lead} \geq 534) \& (Val542_A/Val542_{BCD} + 0.025 \times PeakBin_{lead} \leq 14.75)$ | Pass<br>Fail       | 6112 (77.8%)                                          | 2119 (99.0%)                                         |

### 8.3 Estimating the Interaction Positions

In this section, we describe our methods to estimate the interaction positions for well-measured events using the same  $Val542_A/Val542_{BCD}$  and  $Val542_{lead}/Val542_{near}$  variables and evaluate the accuracy and resolution by comparing them to the true values in simulation. In Section 8.3.1, we describe the linear interpolation methods used to estimate the interaction positions for well-measured events, using  $Val542_A/Val542_{BCD}$  to estimate  $R$  and  $Val542_{lead}/Val542_{near}$  to estimate  $|\Delta\Phi|$ . In Section 8.3.2, we compare the estimated results of  $R$  and  $|\Delta\Phi|$  to the true values, and evaluate the accuracy and resolution. As we will see, all measurements yield correct values within resolution and statistics, but the resolutions are position dependent. We are able to achieve accuracies of down to 0.5 mm in  $R$  and  $1^\circ$  in  $|\Delta\Phi|$ . We note that while similar methods can be used with the phonon energy collected in each channel rather than the pulse shape quantities, the methods here show better resolutions; more detail on that method is described in Appendix D.

#### 8.3.1 Methods for Estimating the Interaction Positions

In this subsection, we describe the linear interpolation methods used to estimate the interactions positions for well-measured events. With values of the two ratios,  $Val542_A/Val542_{BCD}$  and  $Val542_{lead}/Val542_{near}$ , of an event, we can apply a linear interpolation method to estimate both  $R$  and  $|\Delta\Phi|$ . In the first paragraph, we describe the method to estimate  $R$ . In the second paragraph, we describe the method to estimate  $|\Delta\Phi|$ .

Using the  $Val542_A/Val542_{BCD}$  distribution shown in Figure 8.4, we calculate the average (mean) and root mean square (RMS) as a function of  $R$ , as shown in Figure 8.9. As shown in Figure 8.10, given a value of  $Val542_A/Val542_{BCD}$  of an event, a simple linear interpolation between the two nearest points allows us to estimate the corresponding value of  $R$ .

As the ratio of  $Val542_{lead}/Val542_{near}$  is a function of both  $R$  and  $|\Delta\Phi|$ , as shown Figure 8.5, we use a similar technique and make sets of trend lines as a function of  $R$  (with fixed  $|\Delta\Phi|$ ) or  $|\Delta\Phi|$  (with fixed  $R$ ), as shown in Figure 8.11. As illustrated with an example event in Figure 8.12, using the estimated  $R$  obtained from  $Val542_A/Val542_{BCD}$  allows for the construction of an intermediate

trend line of  $Val542_{lead}/Val542_{near}$  vs.  $|\Delta\Phi|$  by linearly interpolating between the two nearest trend lines corresponding to two neighboring  $R$  values. With this interpolated trend line, we then simply estimate  $|\Delta\Phi|$ , following the same procedure used for estimating  $R$ .

Having described the methods to estimate the interaction positions, we next present the results and compare them to the truth values from simulation to estimate the resolution.

### 8.3.2 Comparisons of the Estimated Positions to the True Values in Simulation

In this subsection, we compare the estimated positions to the true values in simulation to evaluate the accuracy and resolution of the methods. For ease of comparison, the estimated and true  $R$  are denoted as  $R_{est}$  and  $R_{true}$ , respectively, while the estimated and true  $|\Delta\Phi|$  are denoted as  $|\Delta\Phi|_{est}$  and  $|\Delta\Phi|_{true}$ . As we will see, for the most part, both  $R$  and  $|\Delta\Phi|$  are typically well measured, with resolutions down to 0.5 mm and  $1^\circ$  respectively, except at the end points. In the first paragraph, we compare the estimated  $R$  to the true values. In the second paragraph, we compare the estimated  $|\Delta\Phi|$  to the true values.

Figure 8.13 shows the correlation between  $R_{est}$  and  $R_{true}$  for all well-measured events. To quantify the estimation accuracy, the mean and RMS of  $R_{est} - R_{true}$  as a function of  $R_{true}$  are shown in Figure 8.14. For all values of  $R$ , the value of  $R_{est}$  is within a standard deviation of the truth value, indicating a fidelity measurement. The resolution, taken to be the RMS, is observed to be a function of the position as shown in Figure 8.14; it reaches a minimum of 0.5 mm in the range  $15 < R_{true} < 20$  mm, while it exceeds 2.0 mm for both small ( $< 5$  mm) and large ( $> 25$  mm)  $R_{true}$ . This result is consistent with the values and variations of  $R_{est} - R_{true}$  as a function of  $R$ , as shown in Figure 8.9. This variation can be understood qualitatively by examining the sharing of Fast Energy between the outer channel (PA) and the combined inner channels (PB+PC+PD); the sharing varies most significantly in the range  $15 < R_{true} < 20$  mm, while less in small and large  $R$ , as briefly illustrated in Figures 8.2a and 8.2b.

Figures 8.15 and 8.16 show the similar results, but for  $|\Delta\Phi|$ . We again see that for most  $|\Delta\Phi|$  measurements, the value of  $|\Delta\Phi|_{est}$  is within a standard deviation of the truth value, indicating a fidelity measurement, though with a few outliers are present. The resolution is observed to be

a function of  $|\Delta\Phi|_{true}$  as shown in Figure 8.16; it decreases from about  $5^\circ$  for  $|\Delta\Phi|_{true} < 20^\circ$  to approximately  $1^\circ$  as  $|\Delta\Phi|_{true}$  increases. This trend can be understood qualitatively from the variation of the ratio  $Val542_{lead}/Val542_{near}$ , as illustrated in Figure 8.5: this ratio exhibits larger variation for smaller  $|\Delta\Phi|_{true}$ , while much smaller variation for larger  $|\Delta\Phi|_{true}$ .

Having used the pulse shape quantities from the various channels as part of methods to both reject poorly-measured events and estimate the position of the well-measured ones as well as evaluated their performance, in the next chapter we proceed to further analyses of the pulse shapes. This includes relative calibration among channels using pulse tails before moving to a comparison of the early portion of pulse shapes between simulated and real data. If we want to use the methods moving forward, we will need to show agreement between simulation in data.



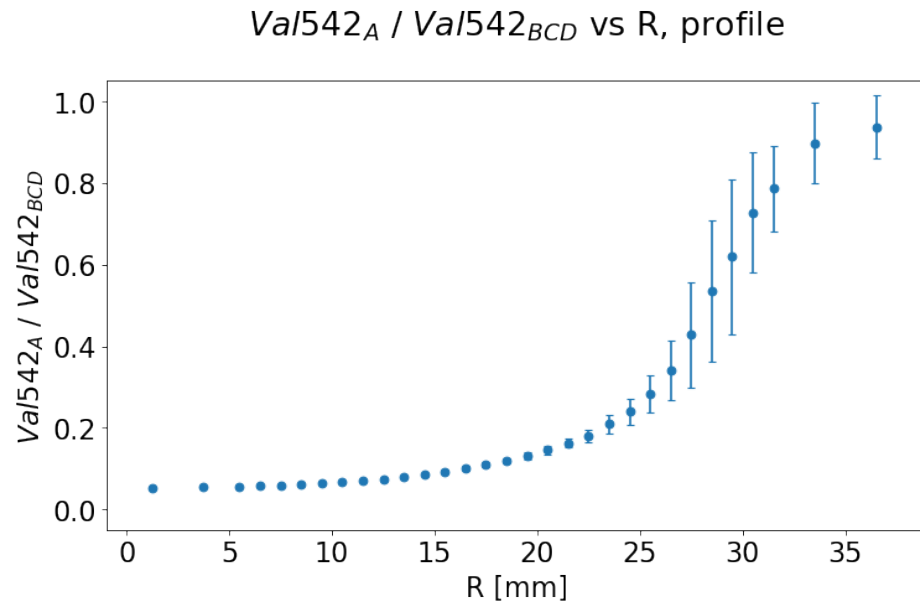


Figure 8.9: This figure shows the average (mean) and root mean square (RMS) of the  $Val542_A/Val542_{BCD}$  distribution shown in Figure 8.4. We show it as it is used to make the interpolation values for estimating  $R$  of interactions.

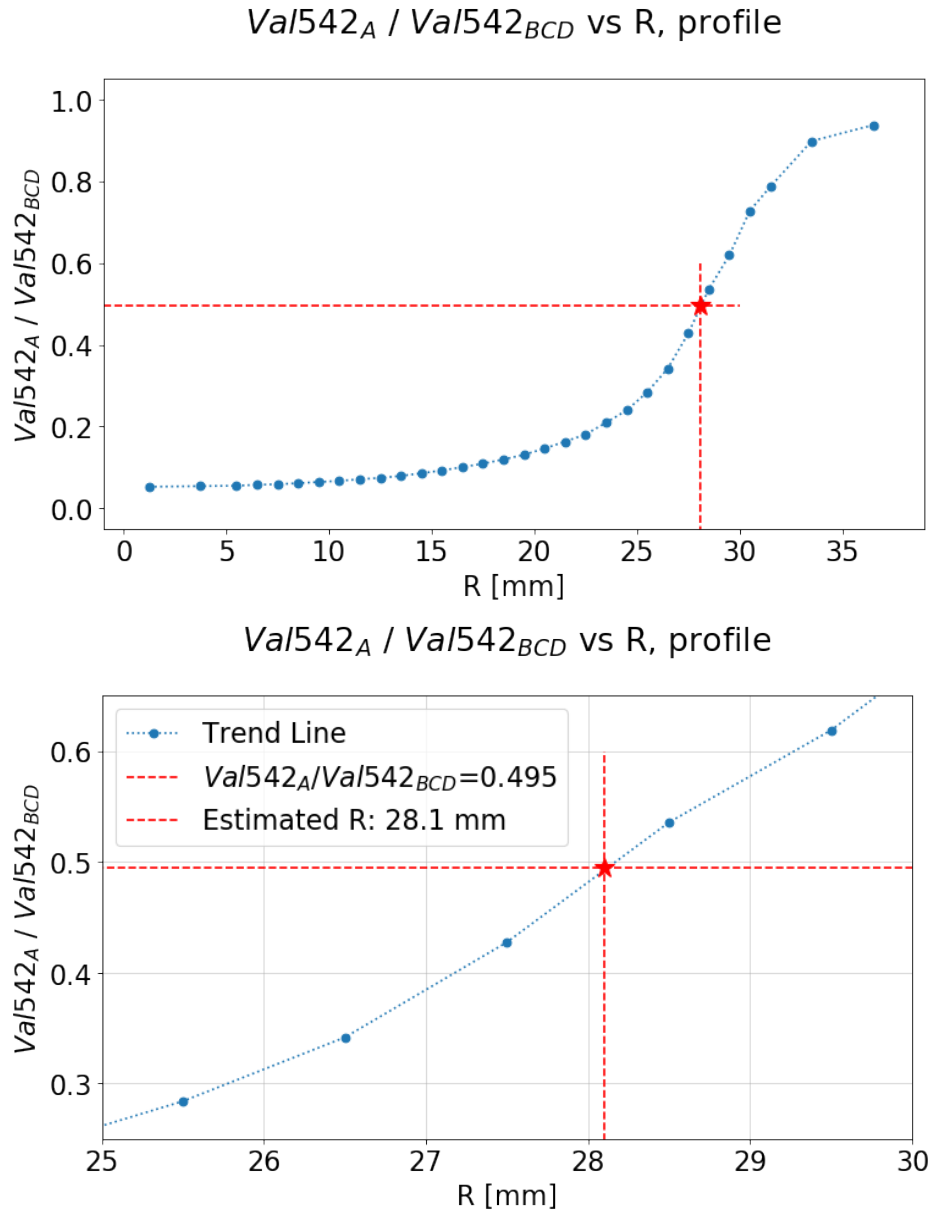


Figure 8.10: This figure shows two simplified versions of Figure 8.9 along with a hypothetical event (red star). We show it to illustrate the implementation of the linear interpolation method based on the binned results to estimate the value of  $R$ . The bottom plot is a zoomed-in view of the top plot, focusing on the region near the red star. Given a  $Val542_A / Val542_{BCD}$  value of 0.495, which lies between  $R = 27.5$  mm and  $R = 28.5$  mm, the  $R$  value for this event is estimated to be 28.1 mm.

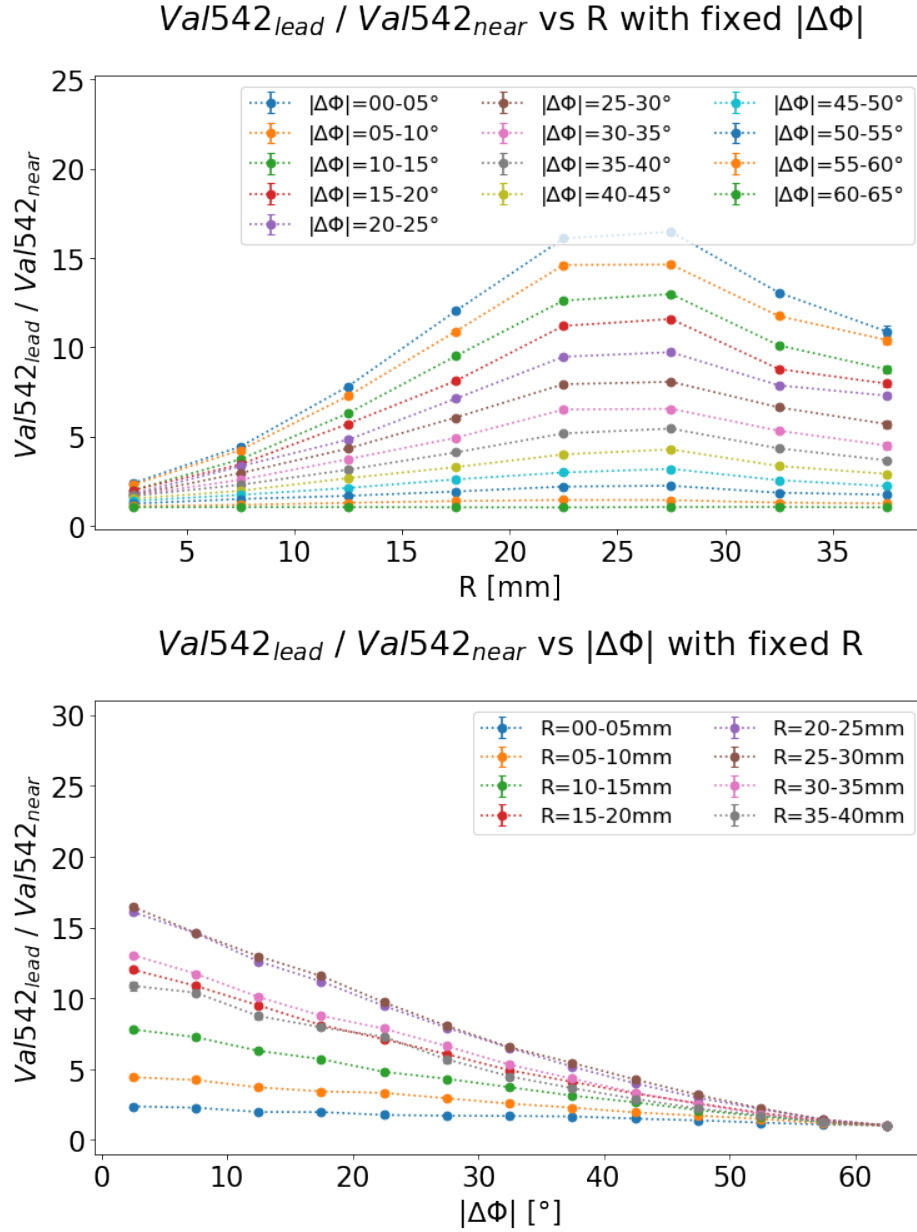


Figure 8.11: This figure shows the values of  $Val542_{lead}/Val542_{near}$  extracted from Figure 8.5, arranged by  $R$  and  $|\Delta\Phi|$ , respectively. We show it to highlight the ratio's dependence on both  $R$  and  $|\Delta\Phi|$ . The top plot displays the ratio as a function of  $R$  for fixed  $|\Delta\Phi|$ , illustrating how it changes with  $R$ . The bottom plot shows that the ratio decreases monotonically with increasing  $|\Delta\Phi|$  for fixed  $R$ , demonstrating its utility for estimating  $|\Delta\Phi|$ , as further illustrated in Figure 8.12.

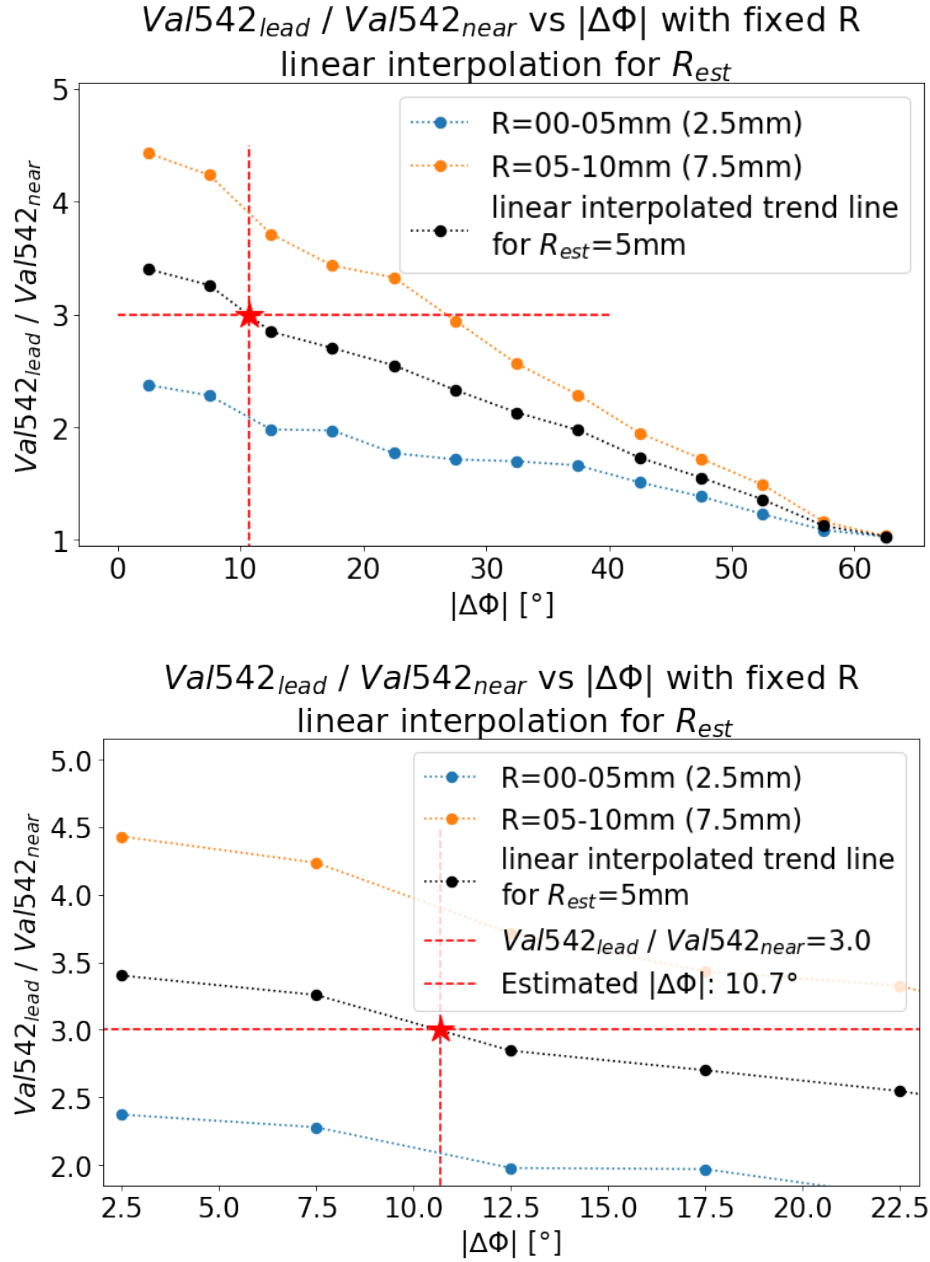


Figure 8.12: This figure shows two trend lines extracted from Figure 8.11 along with an intermediate line obtained via linear interpolation as well as a hypothetical event (red star). We show it to demonstrate the implementation of the linear interpolation method, applying twice to estimate  $|\Delta\Phi|$ . The bottom plot provides a zoomed-in view of the top plot, focusing on the region near the red star. Given an event with an estimated  $R$  of 5 mm, we create a new trend line (black) by applying linear interpolation for the first time, using the two closest lines (blue for  $R = 0-5$  mm; orange for  $R = 5-10$  mm). Then, given a  $Val542_{lead}/Val542_{near}$  value of 3.0, we use the newly interpolated trend line to estimate  $|\Delta\Phi|$ , resulting in a value of  $10.7^\circ$ .

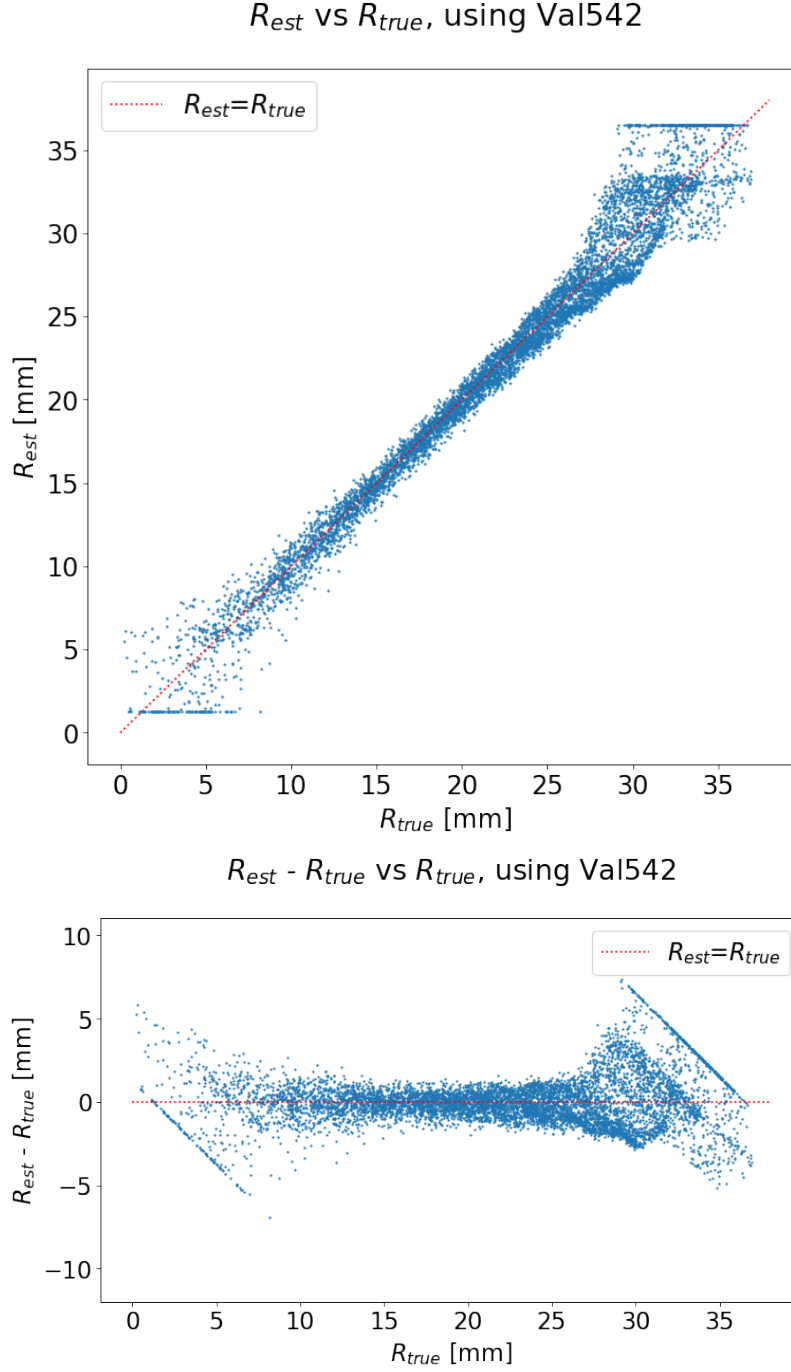


Figure 8.13: This figure shows two comparisons of the estimated values of  $R$  ( $R_{est}$ ) to the true values ( $R_{true}$ ) for the same set of events as in Figure 8.9. We show it to assess the accuracy and resolution of the  $R$  estimation. The top plot displays  $R_{est}$  vs.  $R_{true}$ , while the bottom plot shows  $R_{est} - R_{true}$  vs.  $R_{true}$ . The estimation is accurate within the resolution, but exhibits smaller variation for medium  $R$  values (15–25 mm) where  $Val542_A/Val542_{BCD}$  changes more rapidly.

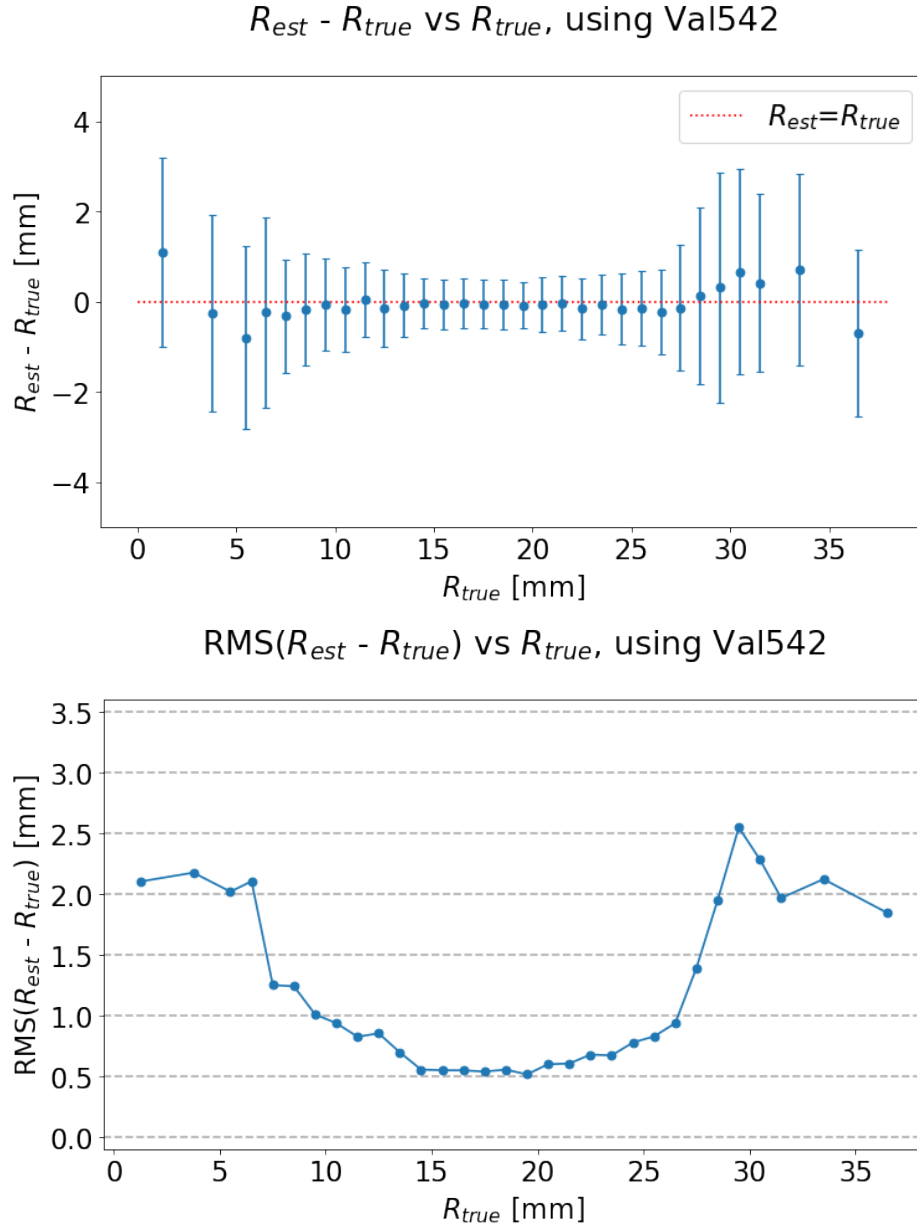
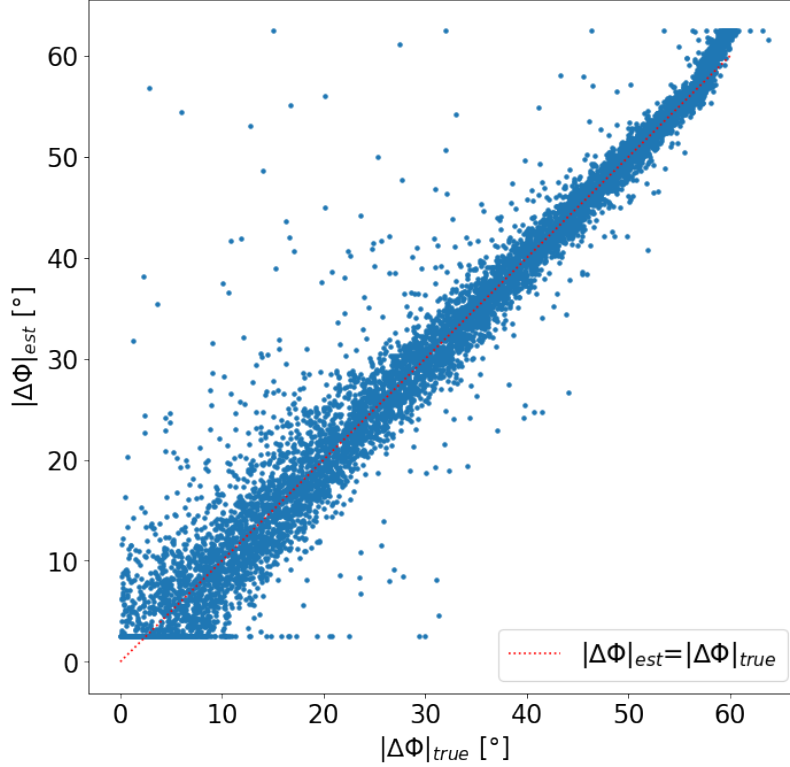


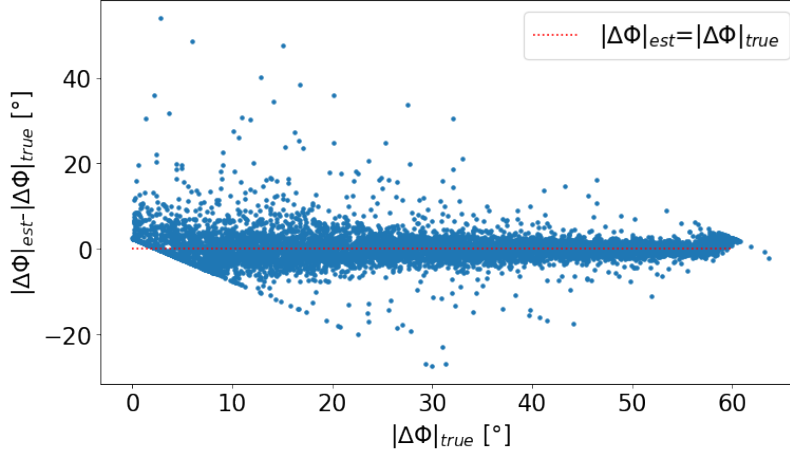
Figure 8.14: This figure shows the same results as Figure 8.13 but plotting the mean and RMS of the binned distributions. We show it to indicate that we get the correct value within uncertainties as well as quantify the resolution as a function of  $R_{true}$ . The top plot is a profile plot, displaying the mean and RMS of  $R_{est} - R_{true}$  within each bin. The bottom plot shows how the RMS varies with  $R_{true}$ ; it decreases from 2.2 mm to 0.5 mm for  $R_{true} < 20$  mm and increases to up to 2.5 mm for  $R_{true} > 20$  mm.

$|\Delta\Phi|_{est}$  vs  $|\Delta\Phi|_{true}$ , using Val542



(a)  $|\Delta\Phi|_{est}$  vs  $|\Delta\Phi|_{true}$

$|\Delta\Phi|_{est} - |\Delta\Phi|_{true}$  vs  $|\Delta\Phi|_{true}$ , using Val542



(b)  $|\Delta\Phi|_{est} - |\Delta\Phi|_{true}$  vs  $|\Delta\Phi|_{true}$

Figure 8.15: This figure shows two comparisons of the estimated values of  $|\Delta\Phi|$  ( $|\Delta\Phi|_{est}$ ) to the true values ( $|\Delta\Phi|_{true}$ ) for the same set of events as in Figure 8.9. We show it to assess the accuracy and resolution of the  $|\Delta\Phi|$  estimation. The top plot displays  $|\Delta\Phi|_{est}$  vs.  $|\Delta\Phi|_{true}$ , while the bottom plot shows  $|\Delta\Phi|_{est} - |\Delta\Phi|_{true}$  vs.  $|\Delta\Phi|_{true}$ . The estimation is accurate within the resolution, but exhibits smaller variation as  $|\Delta\Phi|_{true}$  get larger.

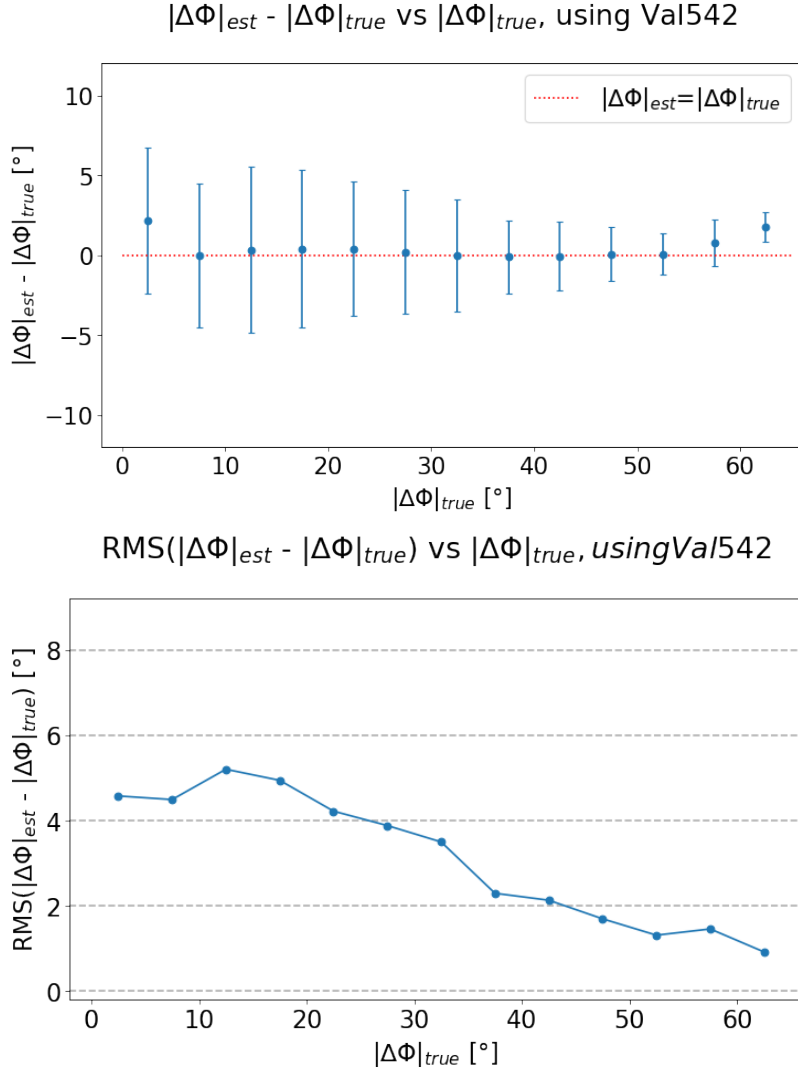


Figure 8.16: This figure shows the same results as Figure 8.15 but plotting the mean and RMS of the binned distributions. We show it to indicate that we get the correct value within uncertainties as well as quantify the resolution as a function of  $R_{true}$ . The top plot is a profile plot, displaying the mean and RMS of  $|\Delta\Phi|_{est} - |\Delta\Phi|_{true}$  within each bin. The bottom plot shows how the RMS varies with  $|\Delta\Phi|_{true}$ ; it decreases from about  $5^\circ$  for  $|\Delta\Phi|_{true} < 20^\circ$  to  $1^\circ$  as  $|\Delta\Phi|_{true}$  gets larger.



## 9. RELATIVE CALIBRATION AND PULSE TAIL STUDY

In this chapter we describe the methods used to take into account the differences between each of the phonon channels in the real detector as described in Section 2.3 and compare the simulation results to both expectations and the real data. Previous analyses have assumed that the amount of Slow Energy is evenly collected by each channel, as described in Section 3.3.1, and if true, we expect both the shapes and magnitudes of the pulses to be the same for all channels at late times. This assumption has been used quantitatively in previous analyses to calibrate the detector outputs by scaling the pulse tails for each channel to be the same [14]. At large enough times, to a good degree of approximation, the shape of the tail can be characterized by a single exponentially falling function. The full calibration procedure can be thought of as having two parts: 1) multiply each pulse shape by a single quantity per channel, bin-by-bin, such that the pulse tails of each of the four channels have identical magnitudes; this is known as a relative calibration, and 2) use the after-relative-calibration pulse shapes as input to the pulse reconstruction procedures using OF algorithms as described in Section 4.1 to get a single multiplicative constant so that the corrected amplitude ( $\text{PTNFamps\_corrected}$ ) can be used to reproduce the total expected phonon energy; this is referred to as the absolute calibration. With this in mind, we focus on the relative calibration procedure, and determine the simple set of constants used to scale the pulses for the individual channels; these quantities will be referred to as calibration constants. One of the significant advantages of our simulation, which sets all channels to be properly calibrated, is that it allows for a check of whether the previously assumed procedure works as expected. Either way, a proper relative calibration will be needed for the real data in order to do the early-time pulse shape comparisons in the next chapter.

Before beginning our description, we note in advance that, as expected, the tails of the pulses from real data do not exhibit identical magnitudes for the hardware reasons described in Section 2.3. However, unexpectedly, we also observe differences between the inner and outer channels in the simulation, for reasons that are not yet fully understood. We will come back to this in later chapters as part of our discussion on potential missing components in the simulations and potentially flawed

analysis assumptions. In Section 9.1, we describe the methods we use for relative calibration and the underlying pulse tail study on which it is based. In Section 9.2, we present the results of the pulse tail study for both simulated and real pulses. In Section 9.3, we describe how we calculate the calibration constants, implement the relative calibration for real data and compare the tails of real pulses after calibration to those of simulated pulses.

## 9.1 Methods of Relative Calibration Based on Pulse Tail Study

In this section, we describe a quantitative study of the pulse tails and the methods developed from them to perform relative calibration on pulses in real data. Extending the work of previous analyses, we define the tail as the falling portion of a pulse after time  $(t) = 2$  ms and characterize its shape using several extracted quantities, as illustrated in Figure 9.1. These quantities are measured for both simulated and real pulses, with the values from simulation serving as references for calibrating the real pulses. By comparing the measured values to expectations, across simulated and real datasets, and among different channels, we establish a foundation for relative calibration, as well as gain insights into the sources of differences. In the first paragraph, we describe the quantities measured on an event-by-event basis for use in the relative calibration. In the second paragraph, we describe our method of choosing the most suitable quantity to use in calibration by analyzing their distributions.

We consider four pulse tail quantities, one directly measured quantity at a fixed time bin and three obtained by fitting the tail with an exponential function of the form  $A \cdot e^{-(t-2)/\tau}$  where  $A$  is the amplitude of the distribution and  $\tau$  is the characteristic fall time. We focus on:

1. *Value@2ms*: the pulse value at 2 ms (at the 1250th time bin of a pulse);
2. *Amplitude*: the fitted amplitude of the tail,  $A$ ;
3. *Fall Time*: the fitted quantity indicating the decreasing rate,  $\tau$ ;
4. *Integral Area*: the integral area under the tail, which can be calculated by  $A \cdot \tau$ .

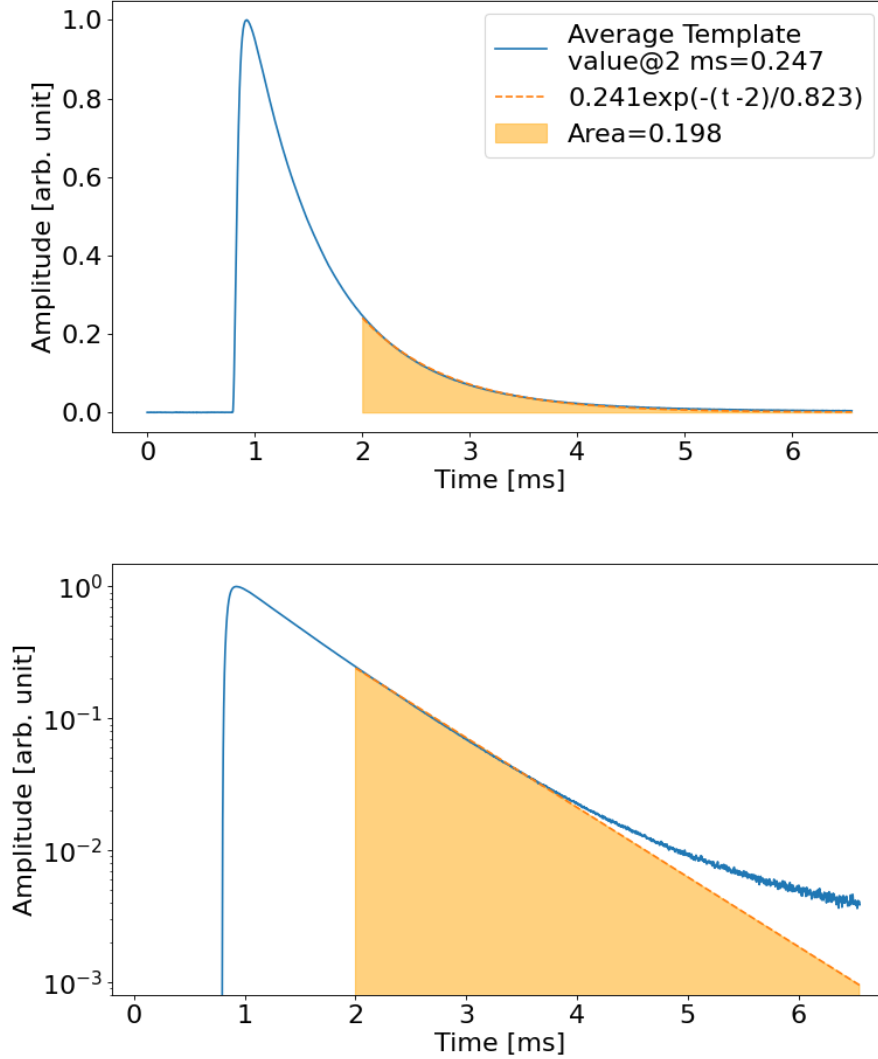


Figure 9.1: This figure shows two versions of the Average Template where we have highlighted the tail region, along with fit results using an exponential function for  $t > 2$  ms in yellow. We show it to illustrate the tail range and shape, and the four quantities used for the pulse tail study and relative calibration with their fitted values listed in the legend. We note that the fitted results are consistent with the tail for  $2 \text{ ms} < t < 4 \text{ ms}$ , but exhibit a clear discrepancy for  $t > 4 \text{ ms}$ . Although the pulse values are relatively small in the later portion of the tail, this discrepancy suggests the shape is a bit more complicated than the exponential function,  $A \cdot e^{-(t-2)/\tau}$ .

While the Average Template is scaled to have a peak value of 1, it can provide a set of unitless expectations that can be scaled. As shown in Figure 9.1, the expected values are:

- *Value@2ms* = 0.247 [norm. unit];
- *Amplitude* = 0.241 [norm. unit];
- *Fall Time* = 0.823 ms;
- *Integral Area* = 0.198 [norm. unit] · ms.

Note the *Fall Time* is unique among the four values as it is independent of any scaling.

To choose the relative calibration quantities, the method begins by making distributions for all four pulse tail quantities in both simulated (well-measured events only) and real data. As they are mostly Gaussian as expected, each is fit with  $A \cdot e^{-(x-\mu)^2/2\sigma^2}$  to determine the values of their mean ( $\mu$ ) and standard deviation ( $\sigma$ ). Since the simulation sets all sensors in a channel to be identical and numerically mimics the electronics response in the same way for all channels, no calibration is needed to account for hardware variations for simulated pulses. The quantity with the smallest fractional standard deviation ( $\sigma/\mu$ ) across channels in the real data is chosen as the calibration reference. To calibrate the real pulses where electronics variations are present, we scale them using the ratio of  $\mu$  from the simulated pulses to the real pulses, ensuring each channel is aligned with the corresponding scale observed in the simulation.

Having described the variables and methods for use in the relative calibration on pulses in the real data, we next present the results of the pulse tail study on both simulated and real pulses followed by the outcomes of the calibration procedure.

## 9.2 Results of the Pulse Tail Study for use in Calibrations

In this section, we present the measurement results of the four pulse tail quantities introduced in the previous section for both simulated and real data, along with comparisons to expectations constructed from the Average Template. For simulated data we use the set of well-measured events in the EPot sample as described in Section 5.2, and for real experimental data we use the subset of

the events with 10 keV energy deposit as described in Section 4.3. As we will see, in simulation, the measured values of  $\mu$  and  $\sigma$  for each of the four pulse tail quantities for the three inner channels (PB, PC and PD) are consistent with each other, reflecting the detector’s symmetric layout shown in Figure 2.3b. In contrast, the outer channel (PA) exhibits slight differences, which are not fully understood but potentially due to the details of phonon reflections off the sidewall or the electric field differences at large radius, which will be further discussed in Section 10.3. On the other hand, in real data, the measured values of  $\mu$  and  $\sigma$  differ significantly not only from the simulations but also from one another across channels. This is not unexpected, given the real-world variations in the hardware.

In Section 9.2.1, we present the measurement results of the four pulse tail quantities for each channel in simulation and compare the results to our expectations and among channels. In Section 9.2.2, we present the measurement results of the four pulse tail quantities for each channel in the real data and compare the results to our expectations and among channels.

### 9.2.1 Results of the Pulse Tail Study for Simulated Data

In this subsection, we present the measurement results of the four pulse tail quantities for each channel in simulation and compare the results to our expectations and among channels. We begin with measurements from the pulses of one example event and then move to the distributions where we determine the values of  $\mu$  and  $\sigma$  of these quantities; the results for all quantities and channels are summarized in Table 9.1. We note in advance that one of the four quantities, *Fall Time*, shows a value higher than expected, which may indicate a problem with the tuning of the parameters in the simulation. In the first paragraph, we consider a single event to illustrate the simulated pulses and our methods. In the second paragraph, we present the distributions for each of the four pulse tail quantities, along with measurements of their corresponding  $\mu$  and  $\sigma$ . In the third paragraph, we comment on the difference between the measured values of the *Fall Time* to the expected value from the Average Template. In the fourth paragraph, we compare the measurement results among channels, in which the three inner channels behave consistently while the outer channel shows small, but statistically significant deviations.

As shown in Figure 9.2, the pulse tails from each of the four channels, using a single event in simulation, visually overlap each other and exhibit an exponential decay, while the earlier portions of the pulses differ due to each channel collecting a different amount of Fast Energy. Figure 9.3 shows the pulses separately along with the best-fit values of the four pulse tail quantities.

The distributions for each of the four pulse tail quantities are shown Figures 9.4 - 9.7. Since each appears to be essentially Gaussian, we fit each distribution with a Gaussian function, from which the  $\mu$  and  $\sigma$  are extracted to enable statistical comparison across channels. The fit results are shown within each figure and summarized in Table 9.1.

The measured values of the *Fall Time*, the only quantity with a specific prediction from the template, are slightly different from the expected value constructed from the Average Template. Each of the inner channels have consistent values of  $\mu$  around 0.834 ms, while PA has a larger value of approximately 0.844 ms. Each of these are larger than the expected value, 0.823 ms. While the consistency between the inner channels is expected, the difference between the inner channels and the outer channel is statistically significant.

For the three other quantities we observe similarities and channel-by-channel differences. Similar to *Fall Time*, we observe that *Value@2ms*, *Amplitude* and *Integral Area* of pulses from the inner channels are consistent with each other within uncertainties, while the outer channel is statistically different. We note that at the time of this writing, while these differences are small they are not understood. We will comment later on some possible explanations, but resolution of these differences is left for future studies.

Having presented the measured values of the four pulse tail quantities for the simulated data, along with comparisons to expectations and among channels, we next present the same set of results and comparisons for the real data in the next subsection.

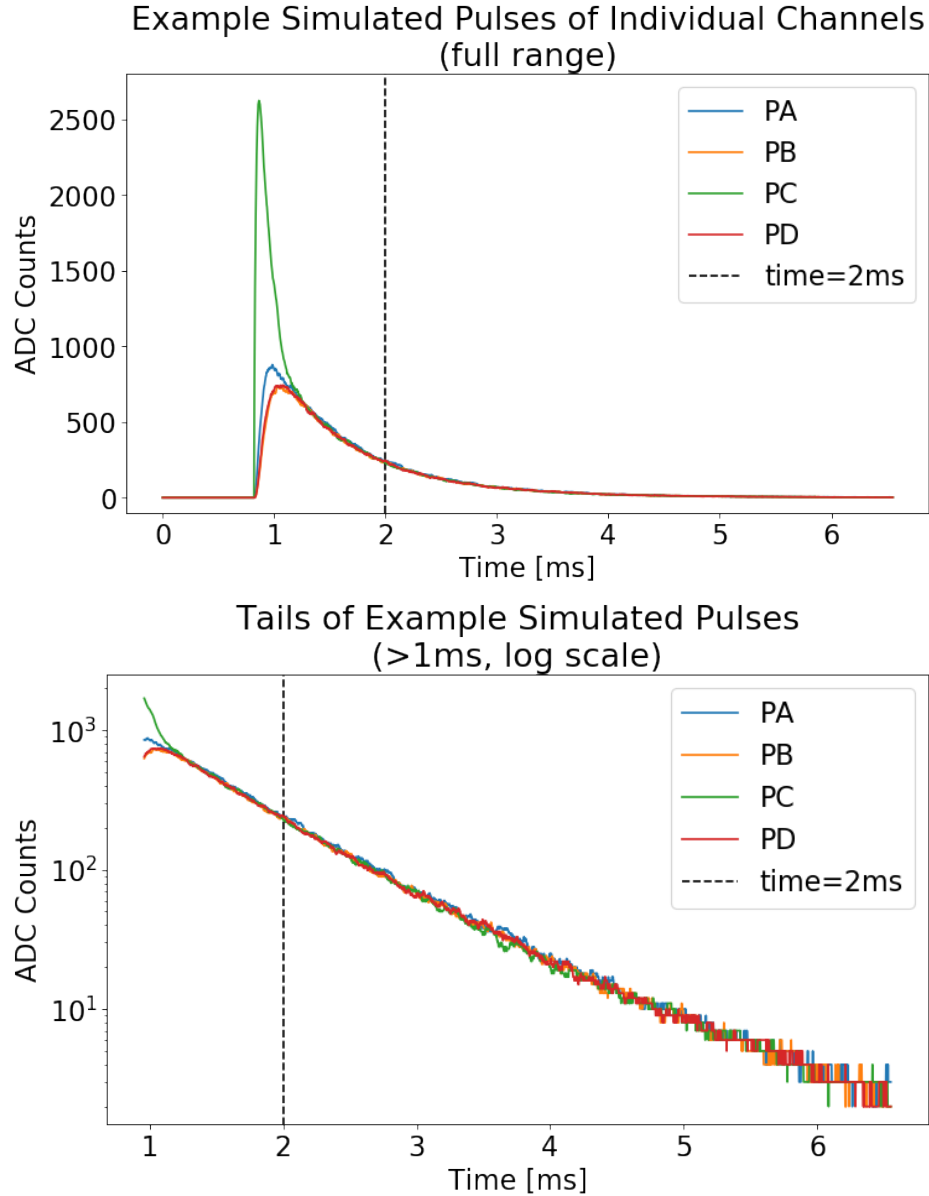


Figure 9.2: This figure shows two versions of the same set of simulated pulses from the four individual channels for a single example simulated event in which the channel PC collects the most energy. We show it to visualize the shape of the pulses with the full range in the top plot as well as the tails ( $t > 2\text{ ms}$ , indicated with the black dashed line) in the bottom plot. From both we see that the tails are visually the same as expected from the prediction that the Slow Energy is evenly shared by the four channels. The pulses at earlier times are different due to different amounts of Fast Energy collected by each. The tails start to converge at  $\sim 1.2\text{ ms}$ , and then overlap with each other until the end of the pulse. We note that PA is slightly different, but not noticeable in this example event.

### Simulated Pulses w/ Exponential Fitting on Tails

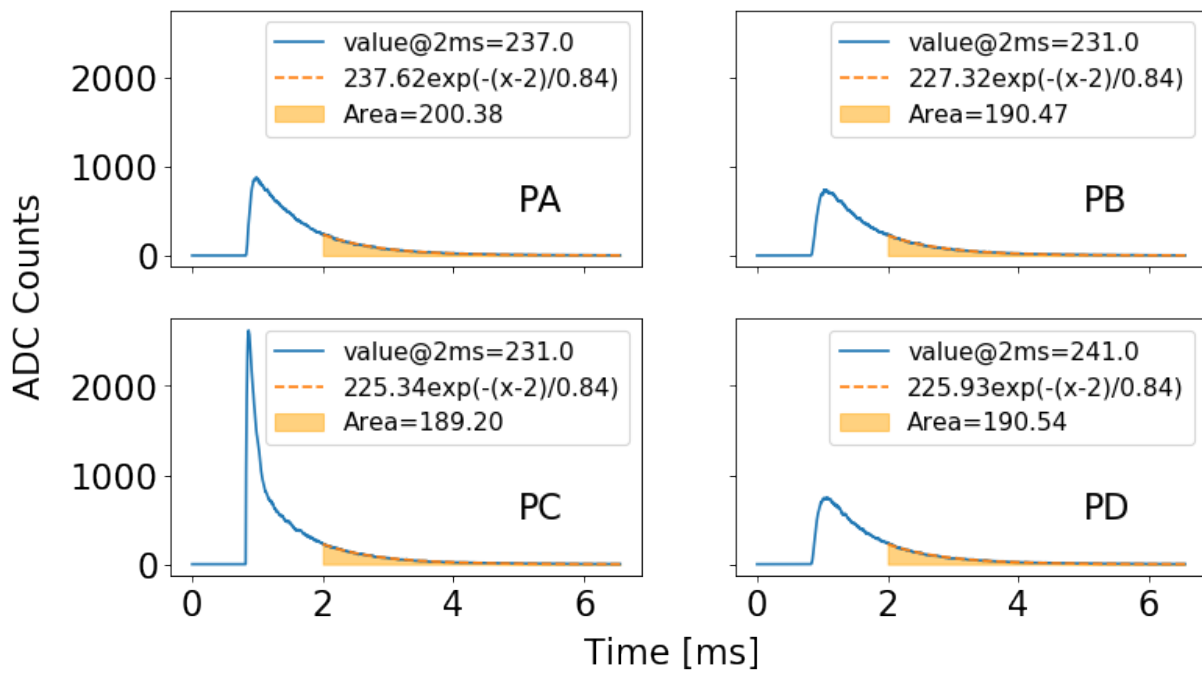


Figure 9.3: This figure shows the same set of pulses as in Figure 9.2 separated by channel along with the results of an exponential fit of the tail regions. We show it to illustrate how the simulated pulse tail is quantified into four single values for use in the relative calibration.



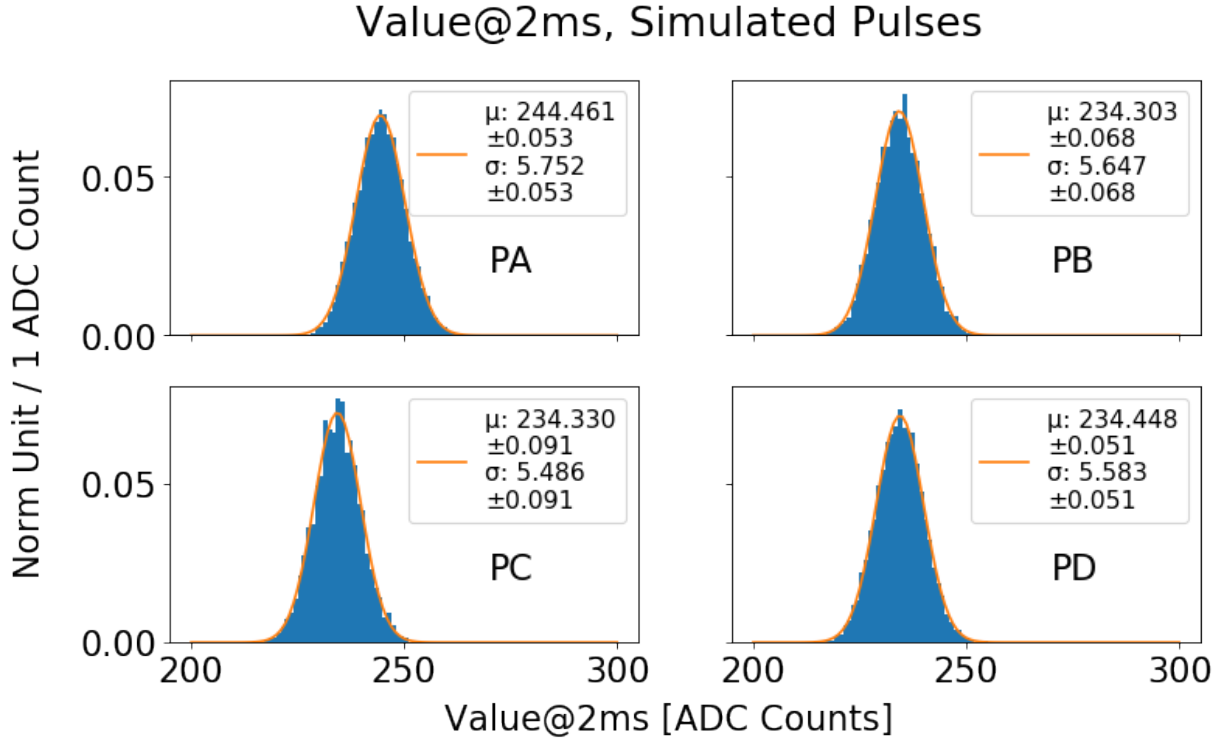


Figure 9.4: This figure shows the distributions of *Value@2ms* of all four phonon channels (PA, PB, PC and PD) for the well-measured events in the EPot sample (simulation), with a Gaussian fit applied to each. We show it to quantify how much *Value@2ms* varies from event to event and from channel to channel, for use in calibration. The Gaussian fit parameters are given in the legends and summarized in Table 9.1. Note that PB, PC and PD have consistent values of  $\mu$  around 234 ADC Counts, while PA has a larger value of approximately 244 ADC Counts. The measurement variation, represented by  $\sigma$ , is similar across all channels, with values around 5 ADC Counts.

## Exponential Fitting Amplitudes, Simulated Pulses

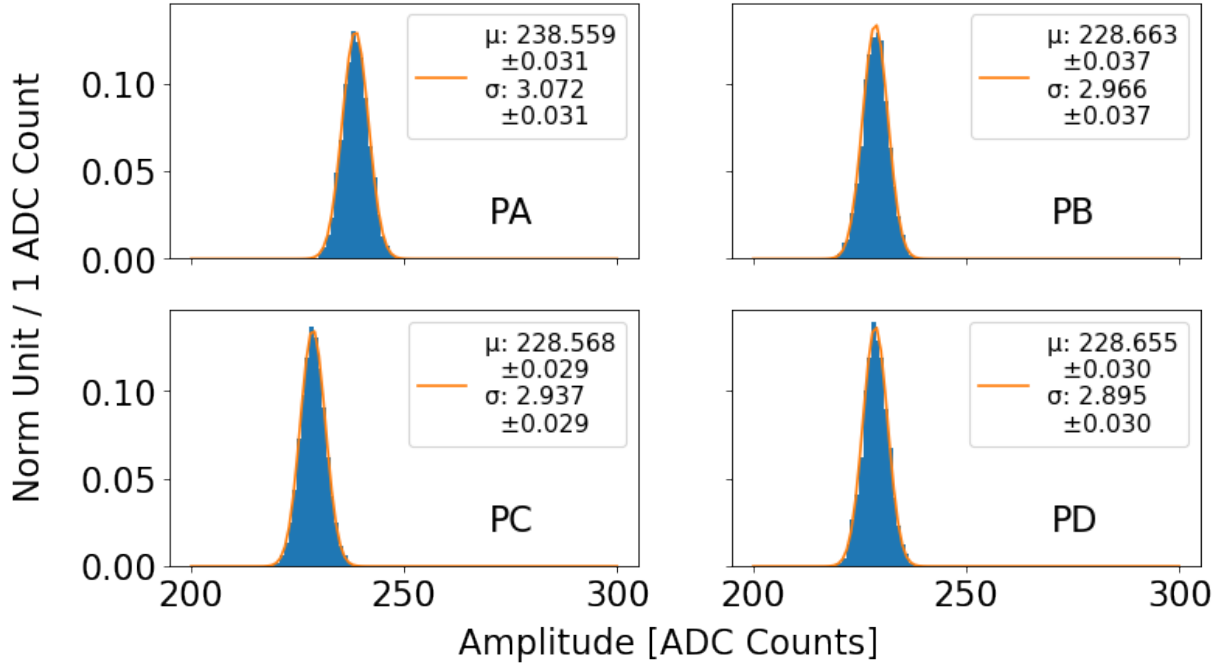


Figure 9.5: This figure is the same as Figure 9.4 but where we show the fitted *Amplitude*. We show it to quantify how much *Amplitude* varies from event to event and from channel to channel, for use in calibration. The Gaussian fit parameters are given in the legends and summarized in Table 9.1. Note that PB, PC and PD have consistent values of  $\mu$  around 228 ADC Counts, while PA has a larger value of approximately 238 ADC Counts. The measurement variation, represented by  $\sigma$ , is similar across all channels, with values around 3 ADC Counts. Compared to *Value@2ms* shown in Figure 9.4, *Amplitude* has a better measurement variation as the fitting process uses more information that helps removes some fluctuations.

## Exponential Fitting Fall Time, Simulated Pulses

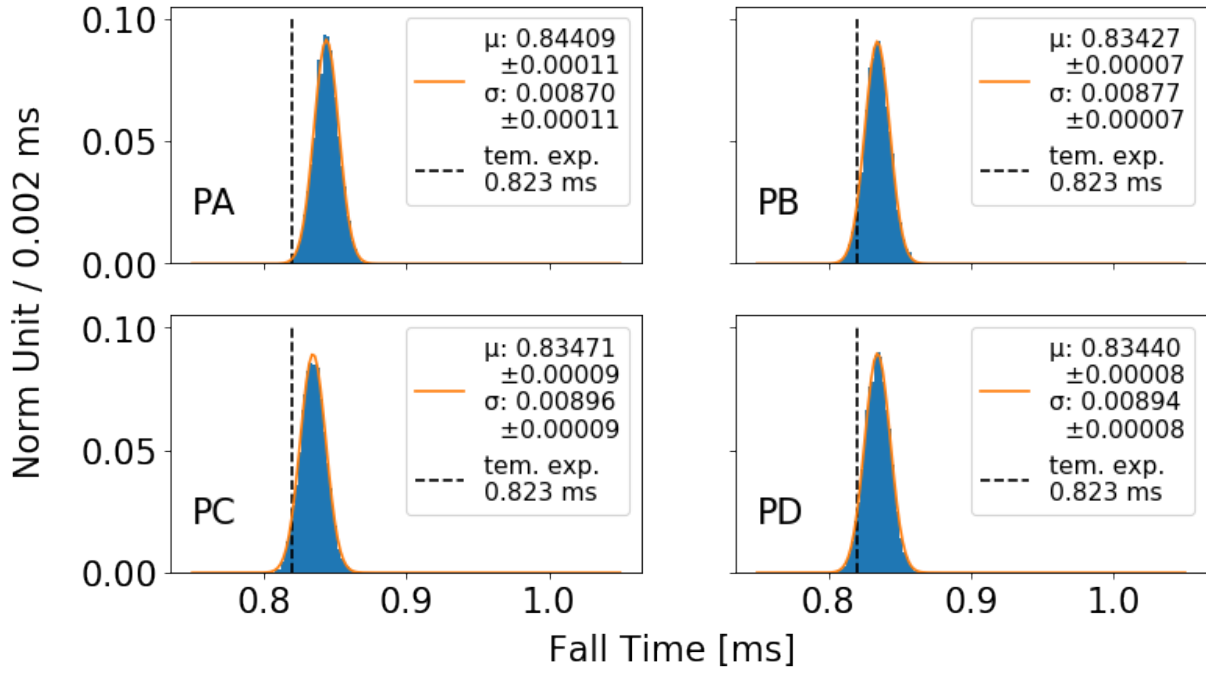


Figure 9.6: This figure is the same as Figure 9.4 but where we show the fitted *Fall Time* and the expected value from the Average Template as shown in Figure 9.1. We show it to quantify how much *Fall Time* varies from event to event and from channel to channel, for use in calibration. The Gaussian fit parameters are given in the legends and summarized in Table 9.1. Note that PB, PC and PD have consistent values of  $\mu$  around 0.834 ms, while PA has a larger value of approximately 0.844 ms, all of which are larger than the expected value, 0.823 ms (black dashed line). The measurement variation, represented by  $\sigma$ , is similar across all channels, with values around 0.009 ms.

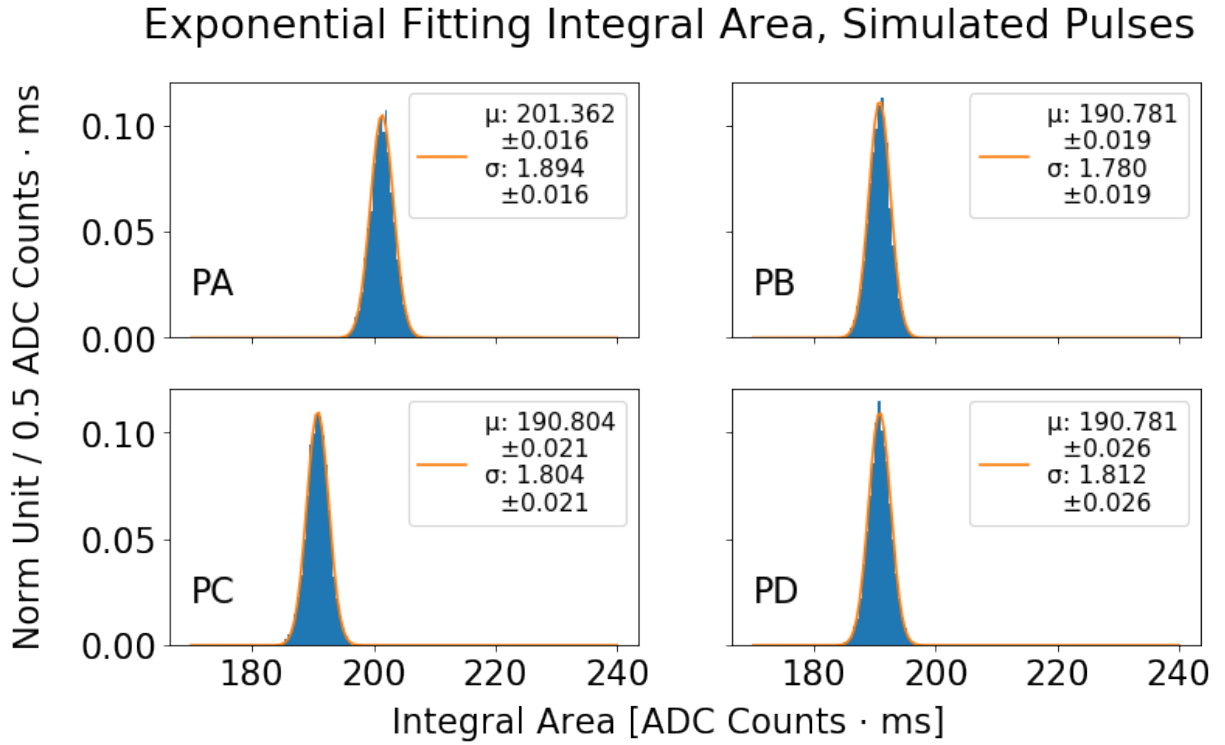


Figure 9.7: This figure is the same as Figure 9.4 but where we show the fitted *Integral Area*. We show it to quantify how much *Integral Area* varies from event to event and from channel to channel, for use in calibration. The Gaussian fit parameters are given in the legends and summarized in Table 9.1. Note that PB, PC and PD have consistent values of  $\mu$  around 190 ADC Counts · ms, while PA has a larger value of approximately 201 ADC Counts · ms. The measurement variation, represented by  $\sigma$ , is similar across all channels, with values around 2 ADC Counts · ms. These results are consistent with those in Figure 9.5 and 9.6 as the *Integral Area* is mathematically equal to the product of *Amplitude* and *Fall Time*.

Table 9.1: This table summarizes all the measured values of  $\mu$  and  $\sigma$  of the fitted Gaussian distributions of *Value@2ms*, *Amplitude*, *Fall Time*, and *Integral Area* for simulated pulses as shown in Figures 9.4 - 9.7. They are compiled here to assess their suitability for relative pulse calibration; note that all uncertainties are statistical only. The fitted quantities (*Amplitude*, *Fall Time*, and *Integral Area*) show smaller measurement variation, indicated by smaller fractional standard deviations ( $\sigma/\mu$ ), compared to *Value@2ms*. While *Integral Area* has the smallest relative standard deviations, *Amplitude* is chosen for relative pulse calibration for the reasons described in Section 9.2.2.

Gaussian Fitting Results on Pulse Tails Quantities (Simulation)

| <i>Value@2ms</i> [ADC Counts]          |                      |                         |                                            |
|----------------------------------------|----------------------|-------------------------|--------------------------------------------|
| Channel                                | $\mu_{Value@2ms}$    | $\sigma_{Value@2ms}$    | $\sigma_{Value@2ms}/\mu_{Value@2ms}$       |
| PA                                     | 244.46±0.05          | 5.75±0.05               | 2.35%                                      |
| PB                                     | 234.30±0.07          | 5.65±0.07               | 2.41%                                      |
| PC                                     | 234.33±0.09          | 5.49±0.09               | 2.34%                                      |
| PD                                     | 234.45±0.05          | 5.58±0.05               | 2.38%                                      |
| <i>Amplitude</i> [ADC Counts]          |                      |                         |                                            |
| Channel                                | $\mu_{Amplitude}$    | $\sigma_{Amplitude}$    | $\sigma_{Amplitude}/\mu_{Amplitude}$       |
| PA                                     | 238.56±0.03          | 3.07±0.03               | 1.29%                                      |
| PB                                     | 228.66±0.04          | 2.97±0.04               | 1.30%                                      |
| PC                                     | 228.57±0.03          | 2.94±0.04               | 1.29%                                      |
| PD                                     | 228.65±0.03          | 2.89±0.03               | 1.27%                                      |
| <i>Fall Time</i> [ms]                  |                      |                         |                                            |
| Channel                                | $\mu_{FallTime}$     | $\sigma_{FallTime}$     | $\sigma_{FallTime}/\mu_{FallTime}$         |
| PA                                     | 0.8441±0.0001        | 0.0087±0.0001           | 1.03%                                      |
| PB                                     | 0.8343±0.0001        | 0.0088±0.0001           | 1.05%                                      |
| PC                                     | 0.8347±0.0001        | 0.0090±0.0001           | 1.07%                                      |
| PD                                     | 0.8344±0.0001        | 0.0089±0.0001           | 1.07%                                      |
| <i>Integral Area</i> [ADC Counts · ms] |                      |                         |                                            |
| Channel                                | $\mu_{IntegralArea}$ | $\sigma_{IntegralArea}$ | $\sigma_{IntegralArea}/\mu_{IntegralArea}$ |
| PA                                     | 201.36±0.02          | 1.89±0.02               | 0.94%                                      |
| PB                                     | 190.78±0.02          | 1.78±0.02               | 0.93%                                      |
| PC                                     | 190.80±0.02          | 1.80±0.02               | 0.95%                                      |
| PD                                     | 190.78±0.03          | 1.81±0.03               | 0.95%                                      |

### 9.2.2 Results of the Pulse Tail Study for Real Data

In this subsection, we present the measurement results of the four pulse tail quantities for each channel in real data and compare the results to our expectations and among channels. As was done in the previous subsection, we begin with measurements from pulses of one example event, as shown in Figures 9.8 and 9.9, and then move to the distributions where we determine the values of  $\mu$  and  $\sigma$  of these quantities for all events, as shown in Figures 9.10 - 9.13 and summarized in Table 9.2. As we will see from the comparisons of these quantities, the pulse tails from all four channels are statistically inconsistent with each other, likely due to differences in the hardware and electronics associated with each channel. We note in advance that even after applying relative calibration, differences remain between the real and simulated pulses, suggesting the presence of additional effects that are not properly modeled in simulation. In the first paragraph, we consider a single event to illustrate the real pulses and our methods. In the second paragraph, we present the distributions for each of the four pulse tail quantities, along with measurements of their corresponding  $\mu$  and  $\sigma$ . In the third paragraph we comment on the similarities and channel-by-channel differences for each of the measurement quantities.

As shown in Figure 9.8, the pulse tails from each of the four channels, using a single event in real data, are visibly different from each other, unlike the consistent overlap observed in the simulated pulses shown in Figure 9.2. Figure 9.9 shows the pulses separately along with the values of the four pulse tail quantities.

The distributions for each of the four pulse tail quantities, along with measurements of their corresponding  $\mu$  and  $\sigma$ , are shown in Figures 9.10 - 9.13. As with the simulation, since each appears to be essentially Gaussian, we fit each with the results given within each figure and summarize the results in Table 9.2.

Both similarities and channel-by-channel differences for each of the measurement quantities are observed. For similarities, we begin by noting that the *Fall Time* values from each channel is close to the expected value (0.823 ms), either slightly higher or lower. This is to be expected as the value is constructed from the Average Template which was derived from the real data. On the other hand,

of particular note is that the *Fall Time* of the outer channel (PA, 0.845 ms) is larger than all the three inner channels (0.808 ms for PB, 0.820 ms for PC, 0.815 ms for PD); this is unexpected relative to the *a priori* assumptions, but is consistent with what is observed in the simulation. For differences, we begin noting that the  $\sigma$  values, as given in Table 9.2, vary between channels, indicating differing noise levels. Additionally, the  $\mu$  values also differ from each other, with the largest discrepancy observed in the *Amplitude* between PC and PD, showing a difference of over  $10\sigma$ . These differences are not only inconsistent with the expected symmetry layout of the three inner channels shown in Figure 2.3b, but also make it so that we can't distinguish between the assumption that the tail amplitude for PA should be the same as for the inner channels, or that the prediction from the simulation should be taken to be more correct.

Having presented the measured values of the four pulse tail quantities for the real data, along with comparisons to expectations, simulation, and among channels, we now proceed to select the appropriate quantities for calculating the relative calibration factors in the next subsection.

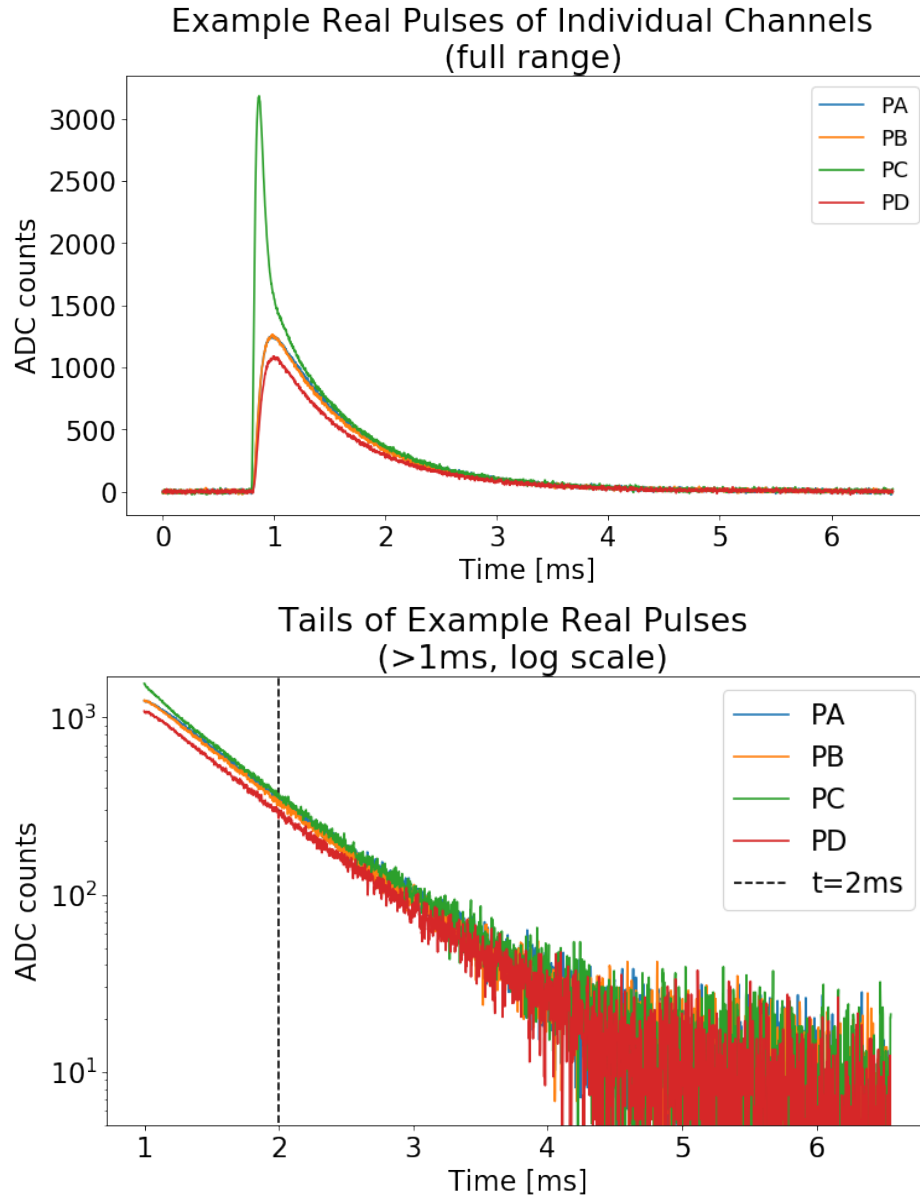


Figure 9.8: This figure is the same as Figure 9.2, but for real data. In contrast to simulated pulses, the real pulses show visually distinct tails across channels, differing from the expectations from the Slow Energy model, but consistent with hardware and readout electronics differences.



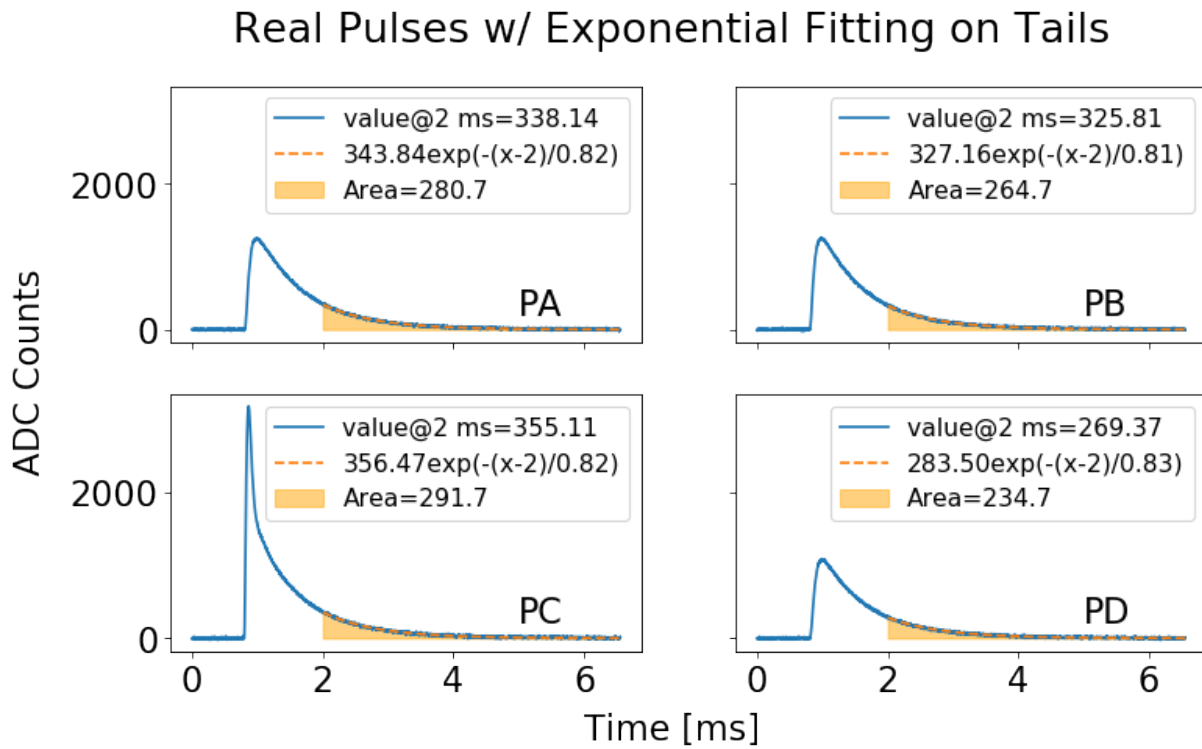


Figure 9.9: This figure is the same as Figure 9.3, but uses the set of pulses from real data shown in Figure 9.8. We show it to illustrate how the real pulse tail is quantified into four single values for comparison to simulation and for use in the relative calibration.

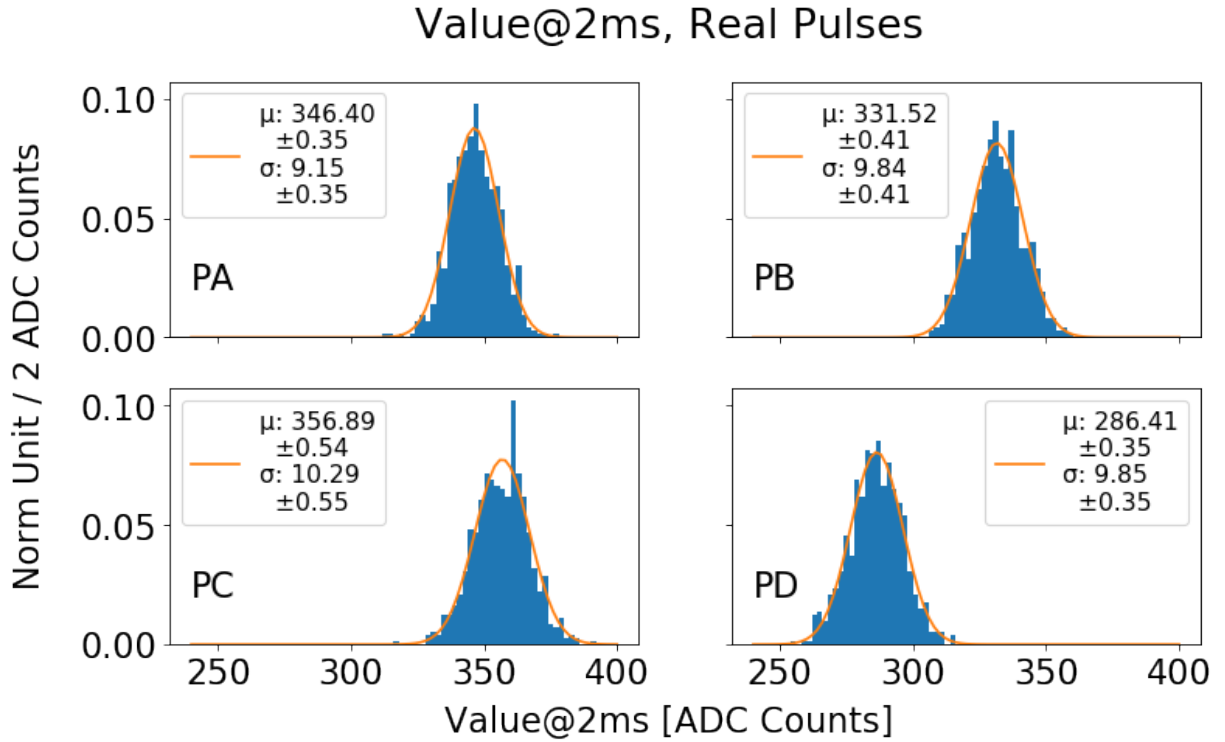


Figure 9.10: This figure uses the same format as Figure 9.4 but with *Value@2ms* for real data. We show it to quantify the variation of *Value@2ms* across events and channels, for comparison to simulation and for use in calibration. Compared to the simulation results, the *Value@2ms* for real data exhibits different  $\mu$  values across channels within the uncertainties, as expected from hardware variation between channels, while  $\sigma$  is similar across all channels, averaging around 10 ADC Counts.

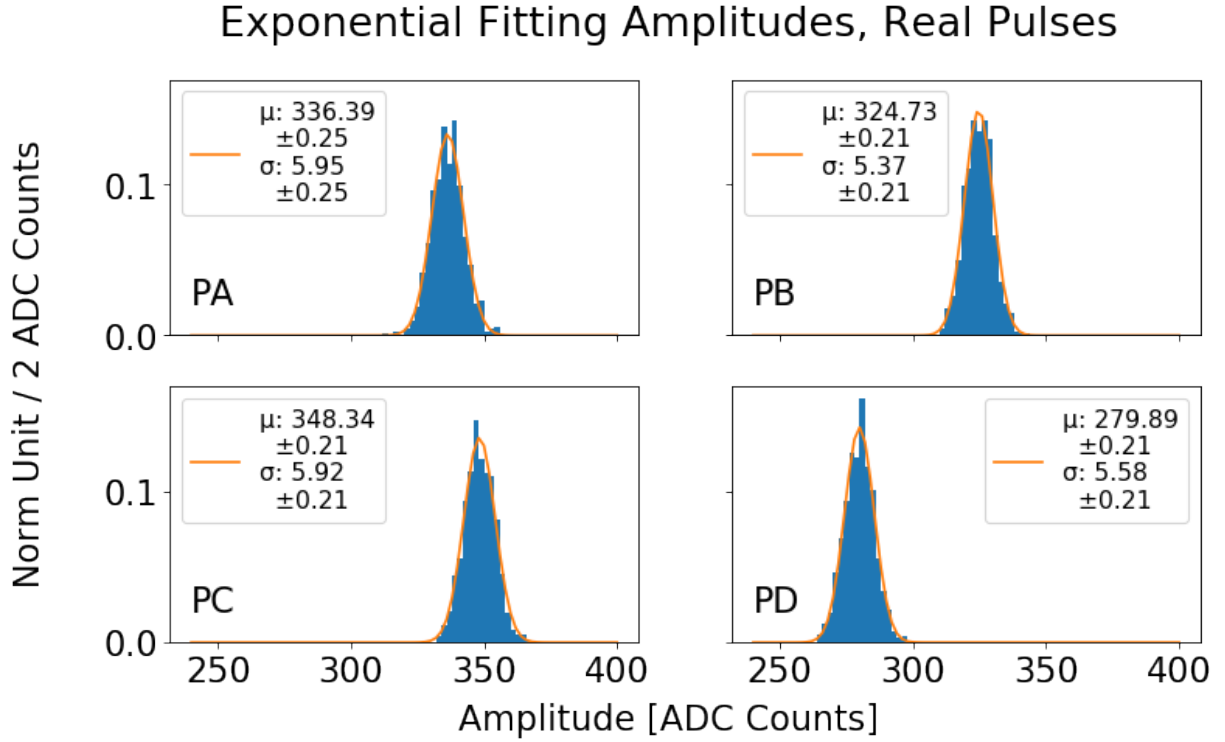


Figure 9.11: This figure uses the same format as Figure 9.5 but with the fitted *Amplitude* for real data. We show it to quantify the variation of *Amplitude* across events and channels, for comparison to simulation and for use in calibration. Compared to the simulation results, the *Amplitude* for real data exhibits different  $\mu$  values across channels within the uncertainties, while  $\sigma$  is similar across all channels, around 6 ADC Counts. Compared to Figure 9.10, it shows the same systematic shifts in the  $\mu$  values, consistent with differences in hardware and electronics.

## Exponential Fitting Fall Time, Real Pulses

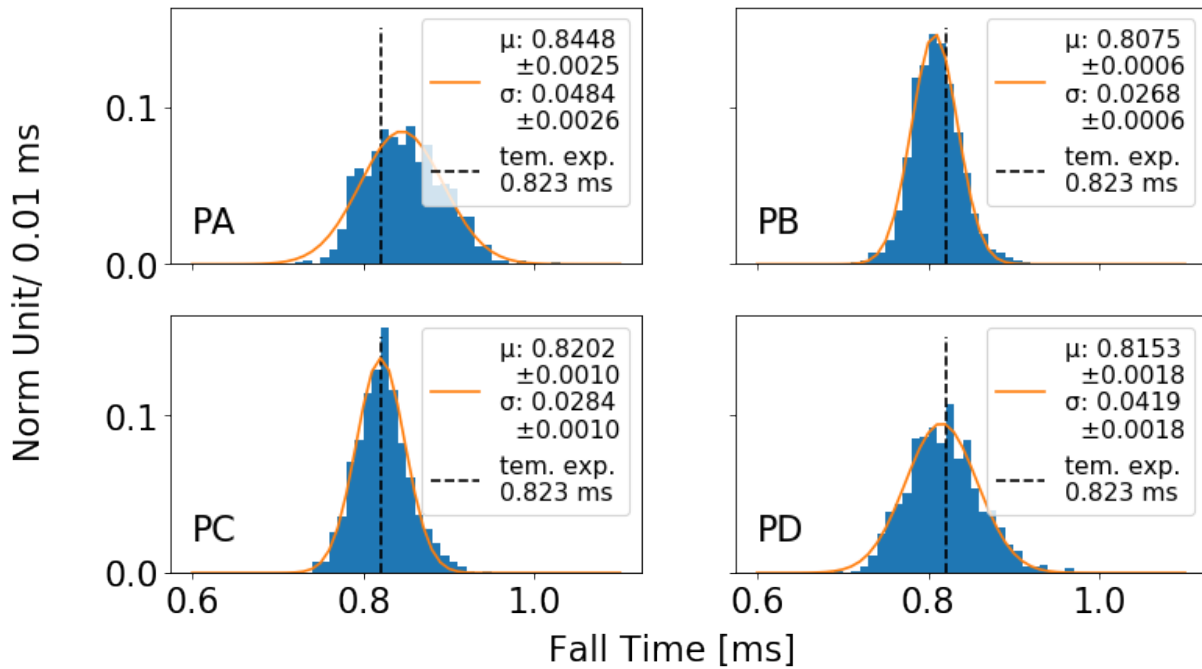


Figure 9.12: This figure uses the same format as Figure 9.6 but with the fitted *Fall Time* for real data, along with the expected value from the Average Template as shown in Figure 9.1. Of particular note are the  $\mu$  values of these distributions. The three inner channels show consistency with each other and the Average Template. This is similar to the observations for simulation results, in that they each have the same values, but different quantitatively. Equally interesting is that, as in simulation, the  $\mu$  value for the outer channel is systematically larger for the three inner channels. Additionally, the  $\sigma$  values also vary across channels, indicating differences in the spread of the distributions.

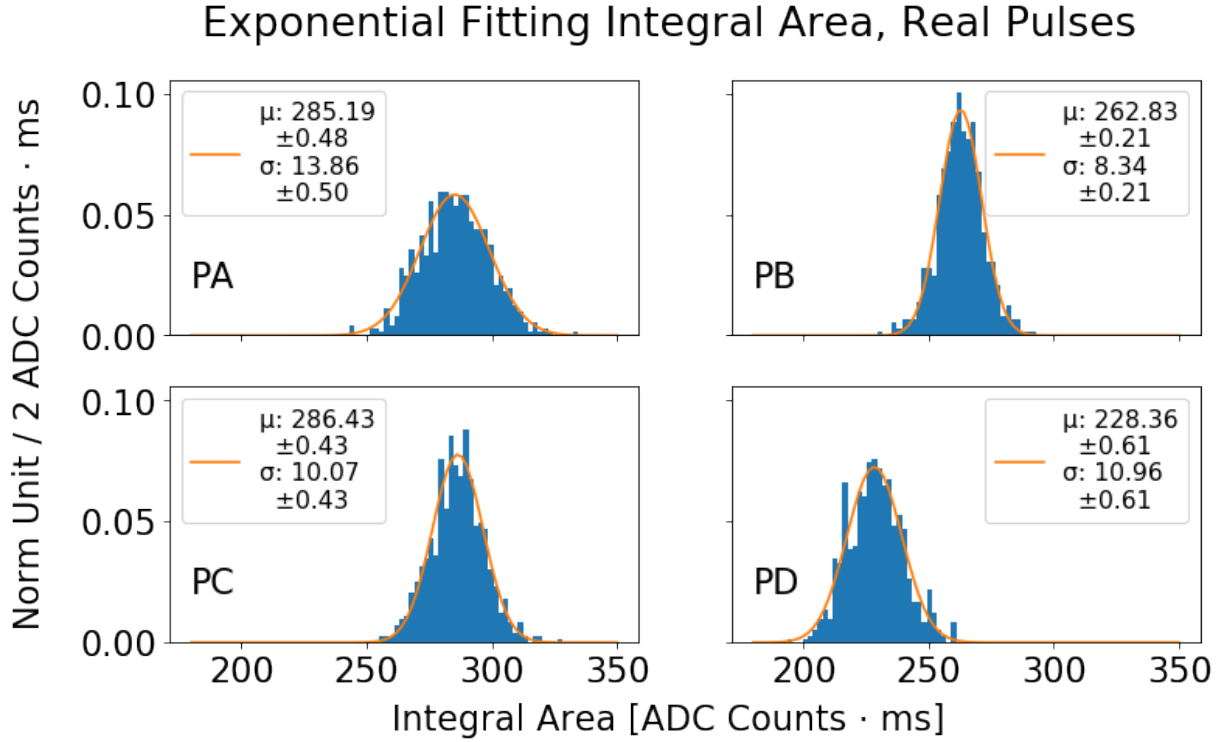


Figure 9.13: This figure uses the same format as Figure 9.7 but with the fitted *Integral Area* for real data. We show it to quantify the variation of *Integral Area* across events and channels, for comparison to simulation and for use in calibration. Compared to the simulation results, we observe that both  $\mu$  and  $\sigma$  values of the fitted *Integral Area* for real data differ across channels within the uncertainties. These results are consistent with those in Figures 9.11 and 9.12 as the *Integral Area* is mathematically equal to the product of *Amplitude* and *Fall Time*.

Table 9.2: This table is the same as Table 9.1, but for real data as shown in Figures 9.10 - 9.13. The fitted *Amplitude* shows the smallest fractional measurement variation and is chosen for relative pulse calibration.

| Gaussian Fitting Results on Pulse Tails Quantities (Real Data) |                      |                         |                                            |
|----------------------------------------------------------------|----------------------|-------------------------|--------------------------------------------|
| <i>Value@2ms</i> [ADC Counts]                                  |                      |                         |                                            |
| Channel                                                        | $\mu_{Value@2ms}$    | $\sigma_{Value@2ms}$    | $\sigma_{Value@2ms}/\mu_{Value@2ms}$       |
| PA                                                             | 346.4±0.3            | 9.15±0.3                | 2.64%                                      |
| PB                                                             | 331.5±0.4            | 9.84±0.4                | 2.97%                                      |
| PC                                                             | 356.9±0.5            | 10.29±0.5               | 2.88%                                      |
| PD                                                             | 286.4±0.3            | 9.85±0.3                | 3.44%                                      |
| <i>Amplitude</i> [ADC Counts]                                  |                      |                         |                                            |
| Channel                                                        | $\mu_{Amplitude}$    | $\sigma_{Amplitude}$    | $\sigma_{Amplitude}/\mu_{Amplitude}$       |
| PA                                                             | 336.4±0.2            | 6.0±0.3                 | 1.77%                                      |
| PB                                                             | 324.7±0.2            | 5.4±0.2                 | 1.65%                                      |
| PC                                                             | 348.3±0.2            | 5.9±0.2                 | 1.70%                                      |
| PD                                                             | 279.9±0.2            | 5.6±0.2                 | 2.00%                                      |
| <i>Fall Time</i> [ms]                                          |                      |                         |                                            |
| Channel                                                        | $\mu_{FallTime}$     | $\sigma_{FallTime}$     | $\sigma_{FallTime}/\mu_{FallTime}$         |
| PA                                                             | 0.845±0.003          | 0.0484±0.003            | 5.73%                                      |
| PB                                                             | 0.807±0.001          | 0.0268±0.001            | 3.32%                                      |
| PC                                                             | 0.820±0.001          | 0.0284±0.001            | 3.46%                                      |
| PD                                                             | 0.815±0.002          | 0.0419±0.002            | 5.14%                                      |
| <i>Integral Area</i> [ADC Counts · ms]                         |                      |                         |                                            |
| Channel                                                        | $\mu_{IntegralArea}$ | $\sigma_{IntegralArea}$ | $\sigma_{IntegralArea}/\mu_{IntegralArea}$ |
| PA                                                             | 285.2±0.5            | 13.9±0.5                | 4.86%                                      |
| PB                                                             | 262.8±0.2            | 8.3±0.2                 | 3.17%                                      |
| PC                                                             | 286.4±0.4            | 10.1±0.4                | 3.52%                                      |
| PD                                                             | 228.4±0.6            | 11.0±0.6                | 4.80%                                      |

### 9.3 Implementing Relative Calibration and Results

In this section, we describe how the relative calibration is implemented based on the results from the pulse tail study presented in the previous section, and compare the calibrated real pulses with those from the simulation. We interpret the channel-by-channel variations in the means of the distributions from the real data as being due to hardware as it is not observed in simulation, except in the case of the outer channel. Therefore, we assume the simulation to be correct and apply a channel-by-channel relative calibration, scaling the values of the real pulses to match those from the simulation. We use the *Amplitude* values for the relative calibration as it has the smallest fractional standard variation ( $\sigma/\mu$ ) in its measurement among the four pulse tail quantities in data as shown in Table 9.2. As we will see, the real pulses after the relative calibration ('real') show closer agreement with the simulated pulses ('sim'); however, residual differences suggest that some factors may still be unaccounted for. In the first paragraph, we explain the choice of *Amplitude* for relative calibration. In the second paragraph, we describe the method of determining the calibration constants and the process of scaling the real pulses using them. In the third and fourth paragraphs, we present and discuss the comparisons of the four pulse tail quantities for the real data after relative calibration, *Amplitude* in the third and *Value@2ms*, *Fall Time*, and *Integral Area* in the fourth. In the fifth paragraph, we propose hypotheses about potential causes that may contribute to the residual differences.

We choose of *Amplitude* for relative calibration as it exhibits the least measurement variation. As listed in Tables 9.1 and 9.2 which summarize the measurement of the four pulse tail quantities, *Amplitude* exhibits the smallest  $\sigma/\mu$  in the real data and is therefore selected for calculating the relative calibration constants. While the smallest variation for any distribution is the *Integral Area* for simulation, *Amplitude* exhibits variations below 2% in both simulated and real data, making it the lowest overall variation among all four pulse tail quantities.

The calibration constants are taken to be the ratio of the  $\mu$  values of *Amplitude* for simulated data to real data, as given in the middle of Tables 9.1 and 9.2 and summarized in the bottom of Table 9.3. For each event in the real data, the pulse is calibrated by multiplying each of its pulse

Table 9.3: This table lists all the fractional standard variations ( $\sigma/\mu$ ) and means ( $\mu$ ) from Tables 9.1 and 9.2, along with the final constants used for the channel-by-channel relative calibration. The compiled values lead us to choose *Amplitude* to calculate calibration constants as it has the smallest  $\sigma/\mu$  from the data.

Comparison of Measurement Fractional Standard Variations ( $\sigma/\mu$ ) for Pulse Tail Quantities

| Channel | <i>Value@2ms</i> |       | <i>Amplitude</i> |       | <i>Fall Time</i> |       | <i>Integral Area</i> |       |
|---------|------------------|-------|------------------|-------|------------------|-------|----------------------|-------|
|         | [ADC Counts]     |       | [ADC Counts]     |       | [ms]             |       | [ADC Counts · ms]    |       |
|         | real             | sim   | real             | sim   | real             | sim   | real                 | sim   |
| PA      | 2.64%            | 2.35% | 1.77%            | 1.29% | 5.73%            | 1.03% | 4.86%                | 0.94% |
| PB      | 2.97%            | 2.41% | 1.65%            | 1.30% | 3.32%            | 1.05% | 3.17%                | 0.93% |
| PC      | 2.88%            | 2.34% | 1.70%            | 1.29% | 3.46%            | 1.07% | 3.52%                | 0.95% |
| PD      | 3.44%            | 2.38% | 2.00%            | 1.27% | 5.14%            | 1.07% | 4.80%                | 0.95% |

Comparison of Measurement Mean ( $\mu$ ) for Pulse Tail Quantities

| Channel | <i>Value@2ms</i> |        | <i>Amplitude</i> |        | <i>Fall Time</i> |        | <i>Integral Area</i> |        |
|---------|------------------|--------|------------------|--------|------------------|--------|----------------------|--------|
|         | [ADC Counts]     |        | [ADC Counts]     |        | [ms]             |        | [ADC Counts · ms]    |        |
|         | real             | sim    | real             | sim    | real             | sim    | real                 | sim    |
| PA      | 346.37           | 244.46 | 336.39           | 238.56 | 0.8448           | 0.8441 | 285.19               | 201.36 |
| PB      | 331.51           | 234.30 | 324.73           | 228.66 | 0.8075           | 0.8343 | 262.83               | 190.78 |
| PC      | 356.94           | 234.33 | 348.34           | 228.57 | 0.8202           | 0.8347 | 286.43               | 190.80 |
| PD      | 286.31           | 234.45 | 279.89           | 228.65 | 0.8153           | 0.8344 | 228.36               | 190.78 |

Calibration Constants based on *Amplitude*

| Channel | Constant | Calculated by |
|---------|----------|---------------|
| PA      | 0.709    | 238.56/336.39 |
| PB      | 0.704    | 228.66/324.73 |
| PC      | 0.656    | 228.57/348.34 |
| PD      | 0.817    | 228.65/279.89 |



values by the corresponding channel's calibration constant. Figure 9.14 shows the same set of pulses as in Figure 9.8, but after applying the relative calibration, confirming that the pulse tails from the four channels are visually aligned.

We start by comparing the values of *Amplitude* between 'real' and 'sim' after calibration. The results are shown in Figure 9.15. While the  $\mu$  values are the same by construction, we note that the distributions are quite similar. We also note that the distributions for the 'real' data are slightly but noticeably broader than those for the 'sim' data, which is attributed to experimental noise that is not included in the simulation.

We next move to comparisons of *Value@2ms*, *Fall Time*, and *Integral Area* quantities, and comment on their differences. As shown in Figure 9.16, the *Value@2ms* in 'real' data are, on average, higher than those in the simulation. As shown in Figure 9.17, the *Fall Time* values in the 'real' data remain unchanged from those in Figure 9.12, as expected as this quantity is unaffected by the relative calibration. As shown in Figure 9.18 for *Integral Area*, we observe a pattern similar to that of *Fall Time*, which is expected since *Integral Area* is numerically equal to *Amplitude*  $\cdot$  *Fall Time*, and *Amplitude* has already been calibrated.

We propose several hypotheses as to why differences remain even after calibration:

- The processes that dominate at late times in the QETs may be more complex than the simple falling exponential from the combination of heating by phonon absorption and cooling to germanium substrate. As shown in Tables 9.1 and 9.2, all *Value@2ms* values are higher than the corresponding *Amplitude*, suggesting a slower decay than modeled or one that changes over time.
- The phonon absorption rates and/or critical temperatures may differ among the QETs in each channel. Although each channel is instrumented with an equal number of phonon sensors, sensor-by-sensor variations in the effective absorption area or sensor coupling may exist in the real detector. In contrast, all phonon sensors are modeled identically in the simulation, which potentially suppresses the realistic variations.

- The variations in the components of the circuits of the sensor readout electronics may result in the different readout values. This effect would be in addition to the previous cause.
- The reflection model, which is set to be fully diffuse in simulation, may need to include specular reflections. Similarly, we expect that some fraction of the phonons that hit a surface may downconvert which is also not currently included.

Having completed the channel-to-channel relative calibration and showed qualitative agreement between the real pulses after calibration, simulation and expectations, we are now ready to move forward with further analyzing the data, despite small residual differences. While all the results must be taken with a grain of salt, in the next chapter, we continue by focusing on the earlier times in the pulse shape to help uncover potential gaps in our understanding of the detector response and the simulation.

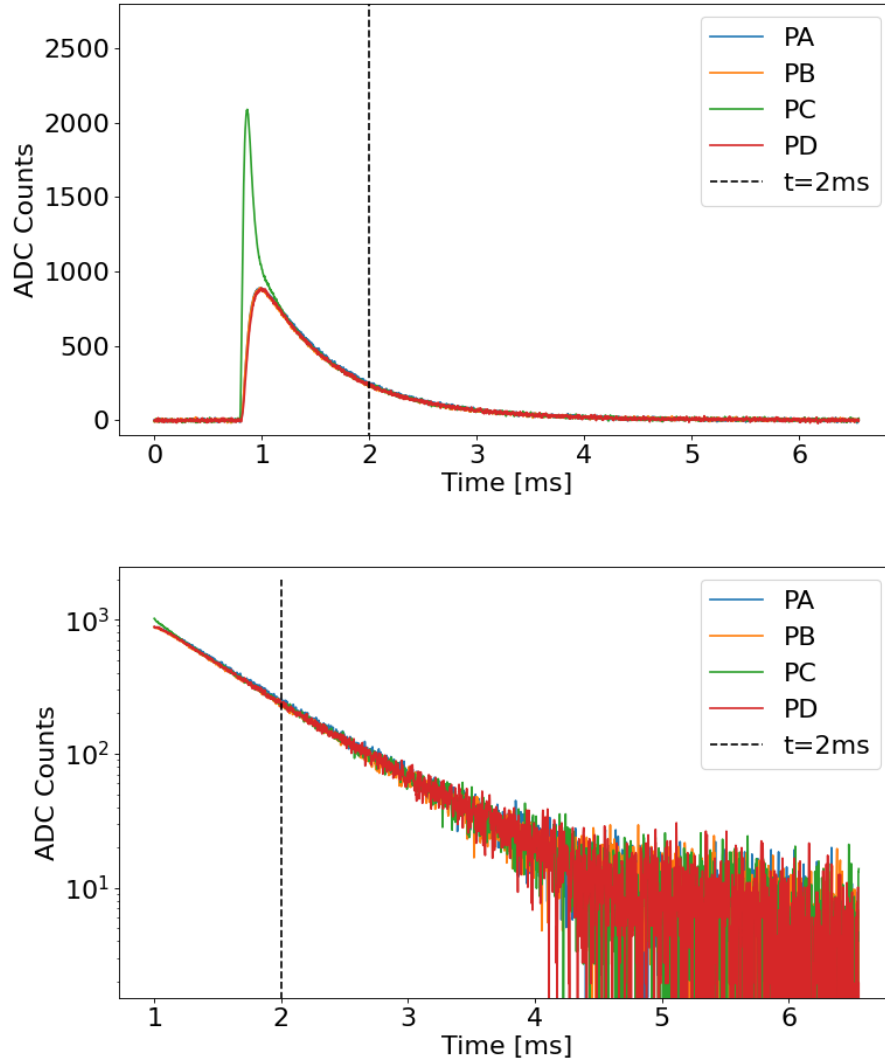


Figure 9.14: This figure shows the same set of real pulse from Figure 9.8 but after relative calibration. We show it to demonstrate that the pulses are well-calibrated, as the tails of the four phonon channels now visually overlap. Quantitative comparisons are shown in Figures 9.15 - 9.18.

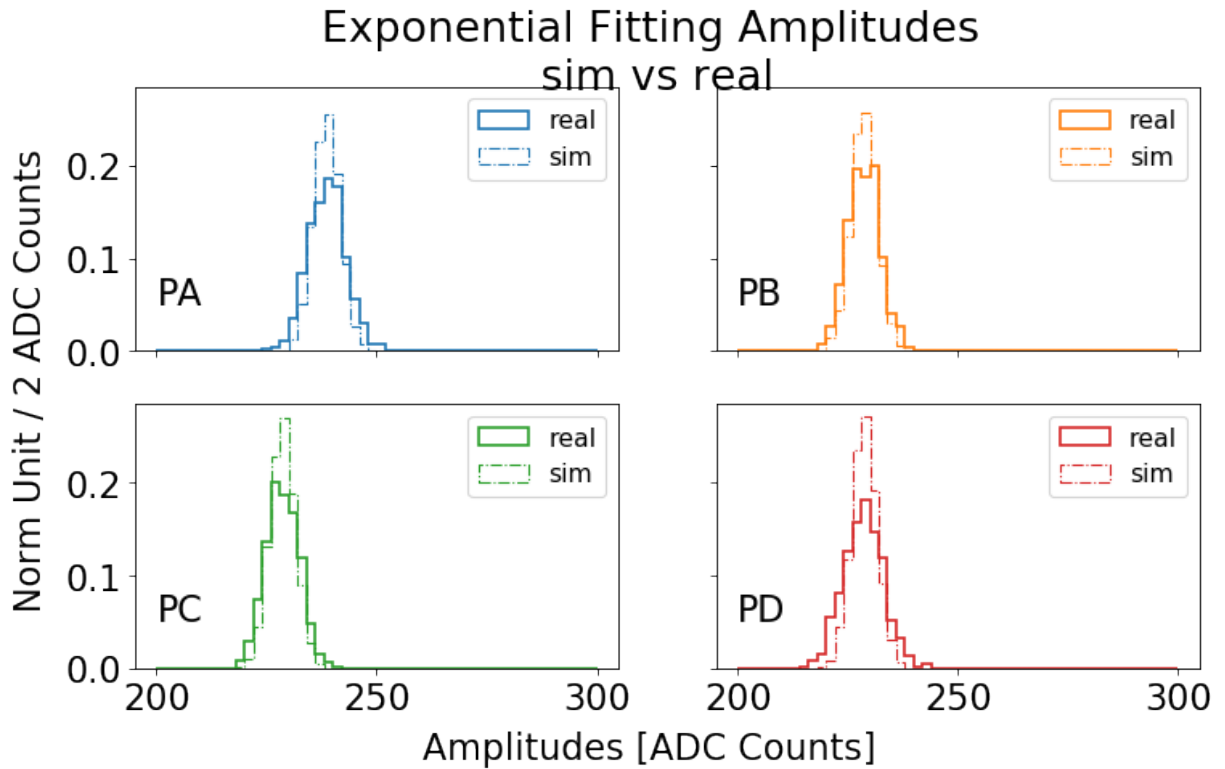


Figure 9.15: This figure shows the the distributions of *Amplitude* for simulated pulses ('sim,' solid lines) and calibrated real pulses ('real,' dashed lines) from the four individual channels (PA, PB, PC, and PD, represented by blue, yellow, green, and red, respectively). We show it to demonstrate that the *Amplitude* in 'real' aligns well with 'sim,' as expected, since *Amplitude* values were used for calibration. The 'real' data shows a broader distribution due to real-world noise, which is not included in the simulated data.

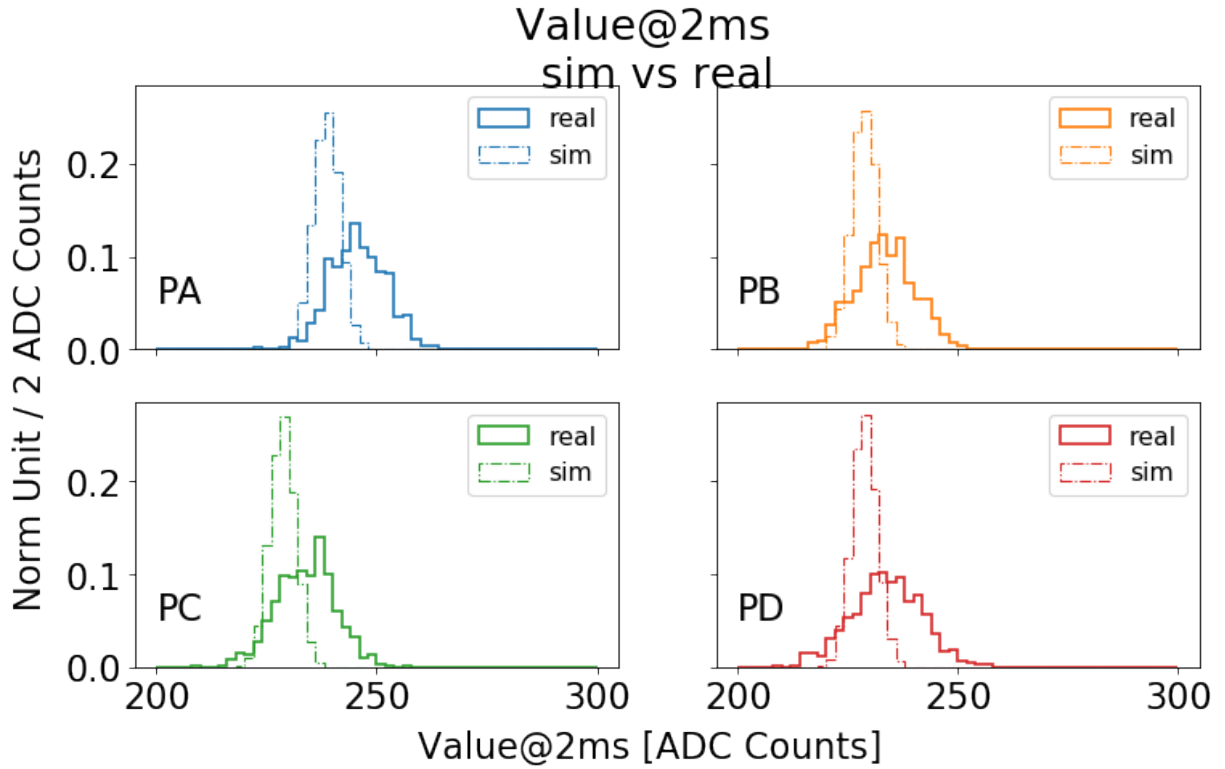


Figure 9.16: This figure shows the same set of plots as Figure 9.15 but for *Value@2ms*. Together with Figures 9.17 and 9.18, we show it to illustrate the consistencies and differences between simulated pulses and calibrated real pulses. The centers of the ‘real’ distributions across all channels are shifted higher compared to simulation, and the ‘real’ distributions are wider due to additional real-world noise.

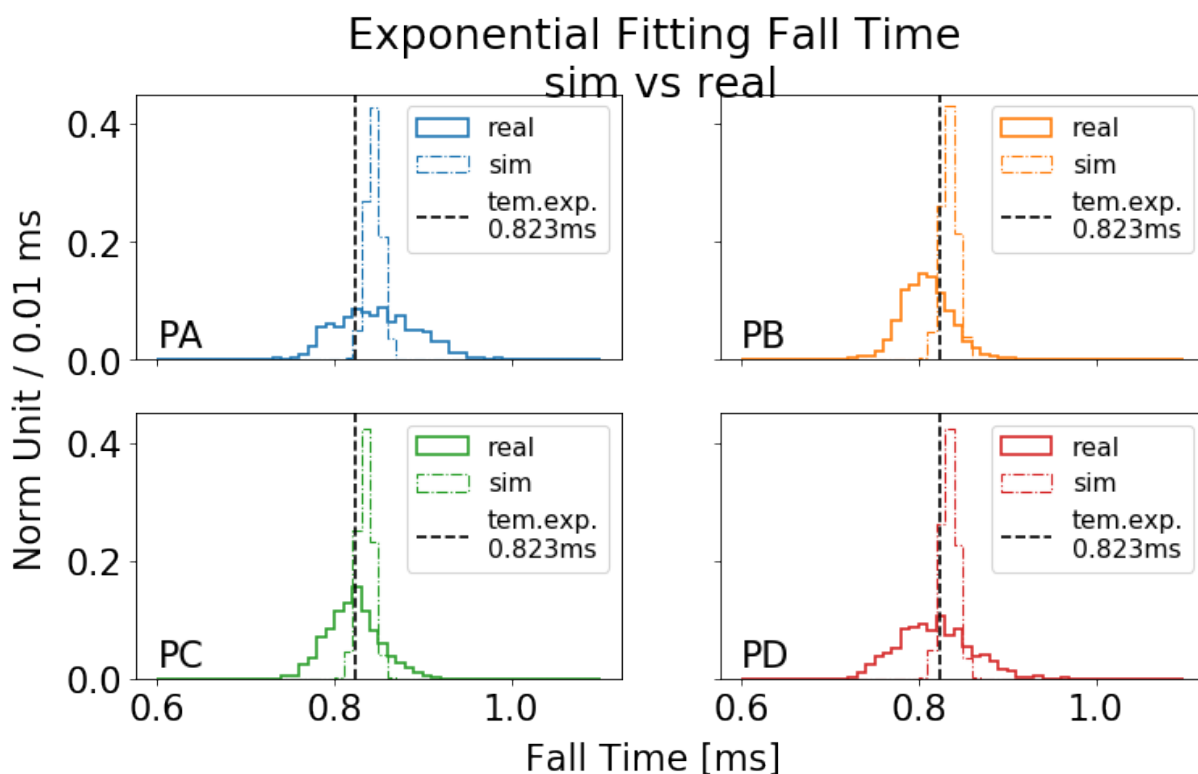


Figure 9.17: This figure shows the same set of plots as Figure 9.15 but for *Fall Time*, along with the expected value, 0.823 ms, constructed from the Average Template. Together with Figures 9.16 and 9.18, we show it to illustrate the consistencies and differences between simulated pulses and calibrated real pulses. Of particular note is that the means of the ‘sim’ distributions are quite narrow and systematically above both the expectation from the template, and often above those of ‘real.’ The ‘sim’ distributions are also systematically narrower than the ‘real’ which may be due to additional real-world noise, or may have other contributions.

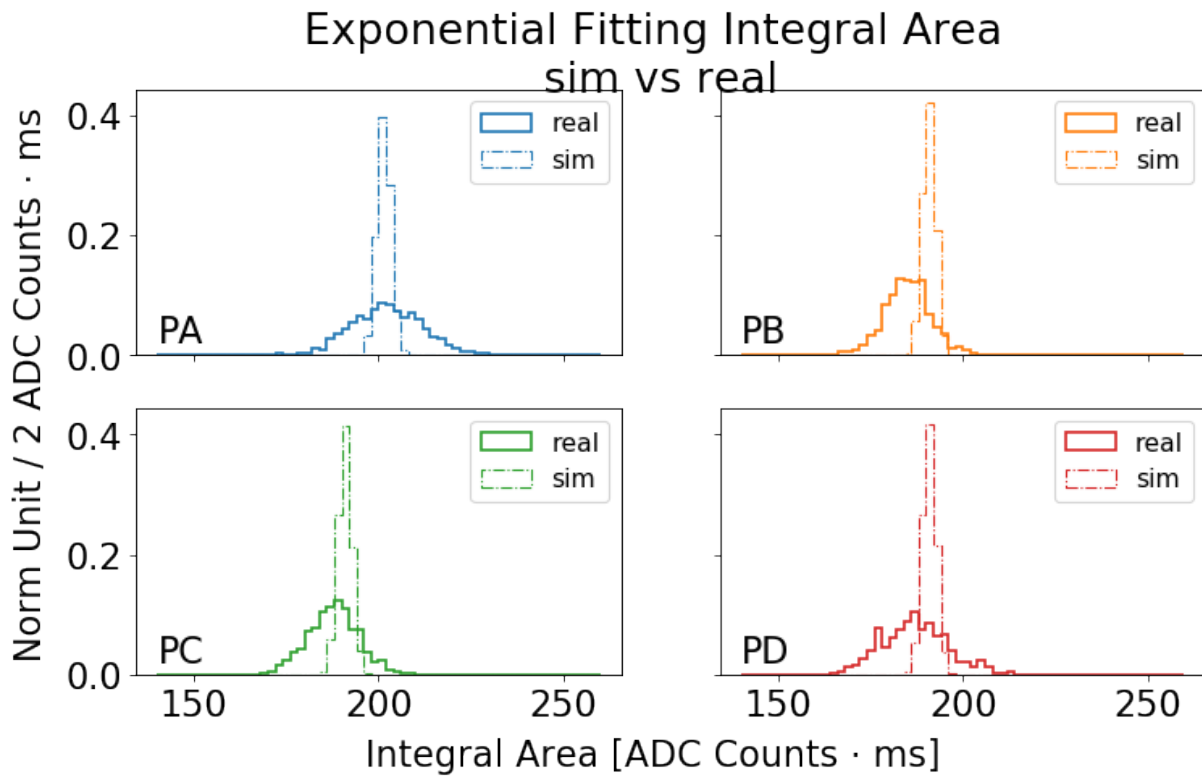


Figure 9.18: This figure shows the same set of plots as Figure 9.15 but for *Integral Area*. Together with Figures 9.16 and 9.17, we show it to illustrate the consistencies and differences between simulated pulses and calibrated real pulses, showing similar patterns to those observed in Figure 9.17. Note that *Integral Area* is mathematically equal to *Amplitude* multiplied by *Fall Time*.

## 10. COMPARISON OF SIMULATED PULSES TO REAL EXPERIMENTAL PULSES AFTER RELATIVE CALIBRATION

In the previous chapter, we described the channel-by-channel relative calibration methods on real pulses and compared the tails of the real pulses after calibration ('real') to the simulated ones ('sim'). Although small differences remain, the tails of both are qualitatively similar enough to warrant further comparison. In this chapter, we compare the early-time parts of the pulses which are most affected by the amount of Fast Energy; the set of plots are enumerated in Table 10.1 and use the set of pulse shape quantities introduced in Chapter 8. Figure 10.1 shows a representative example which is typical for our results: we observe qualitative agreement but quantitative differences. Although the reasons for these differences are not yet fully understood, we propose several hypotheses as an initial step toward an explanation.

In Section 10.1, we describe the comparison methods, where we use three of the pulse shape quantities from Chapter 8 to compare pulses from combined and individual channels. In Section 10.2, we compare the results from 'sim' and 'real', from which we notice that the most significant differences occur in events for large radii. In Section 10.3, we propose several hypotheses to potentially explain these differences, along with some supporting preliminary results.

### 10.1 Comparison Methods and Expectations

In this section, we describe the methods used to compare the early portion of the pulse shapes between 'sim' with 'real' along with our expectations. We use the three pulse shape quantities *Val542*, *Peak Bin* and *Peak Value*, as illustrated in Figure 10.1. Comparisons are made for combinations of channels as well as for individual channels as enumerated in Table 10.1. To facilitate the description we will use the following naming conventions: 1) the summed pulse from all four phonon channels (PA+PB+PC+PD), will be referred to as the total pulse; 2) the pulse from the outer channel (PA) and the summed pulse from the three inner channels (PB+PC+PD), will be referred to as the outer pulse and the inner pulse, respectively; 3) the pulse from each individual channel (PA, PB, PC, PD), will



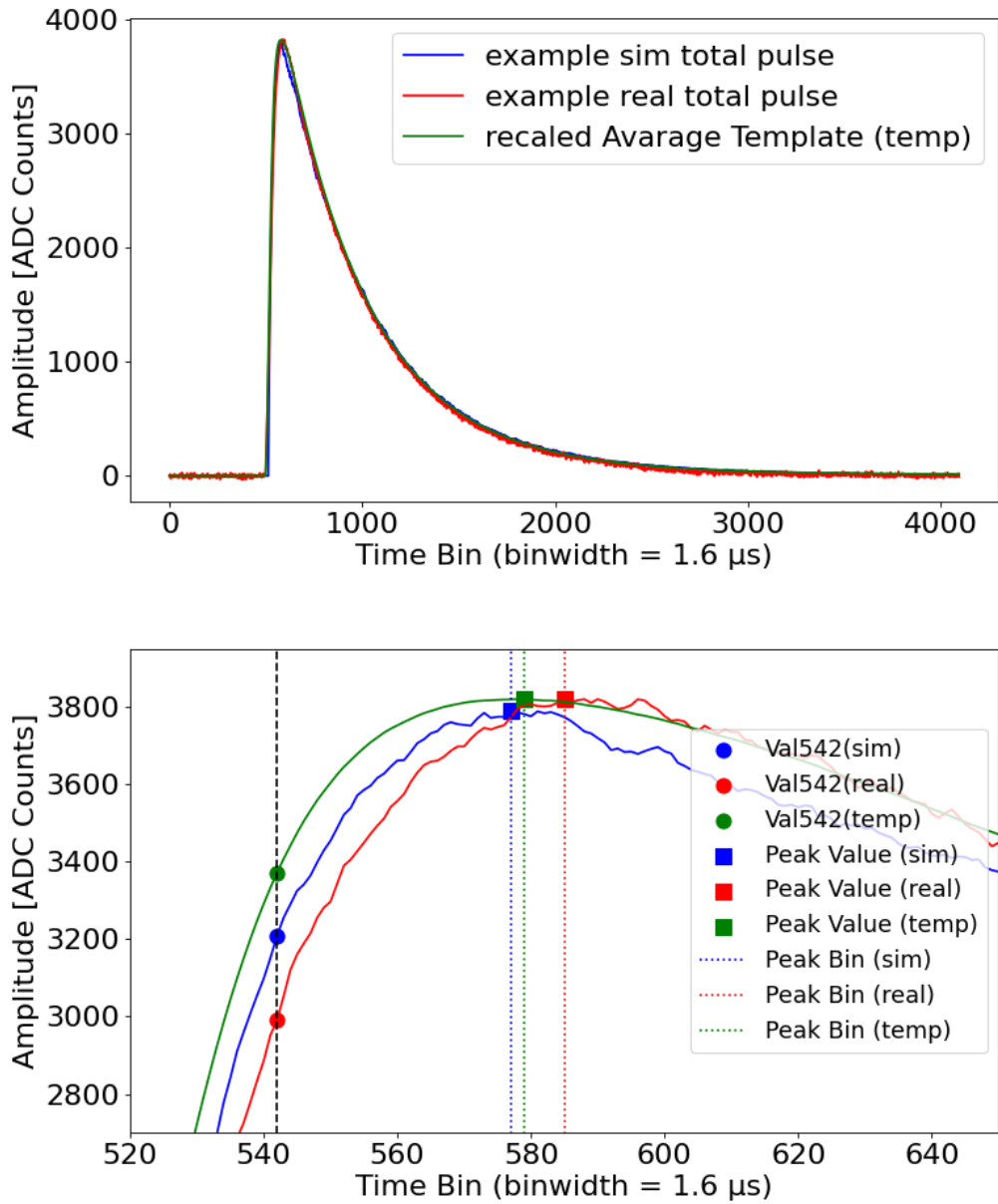


Figure 10.1: This figure shows two versions of three example pulses and compares the pulse shape quantities, *Val542*, *Peak Bin* and *Peak Value*. We show it to illustrate the qualitative similarities but quantitative differences. Each are total pulses with one randomly simulated ('sim,') shown in blue, one real-after-relative-calibration ('real,') shown in red, and the Average Template ('temp') shown in green after rescaling to have the same *Peak Value* as 'real'. The top plot displays the whole trace and while they are visually similar, the zoomed-in version of the peak region in the bottom plot reveals noticeable differences in the three pulse shape quantities.

Table 10.1: This table lists the four pulse shape quantity distributions and the three pulse quantities, along with figure numbers for each. We show it as a road map for the comparisons to be made in Section 10.2.

| channels included<br>in the comparison \ pulse shape<br>quantity | <i>Val542</i>               | <i>Peak Bin</i> | <i>Peak Value</i> | <i>Peak Value vs.<br/>Peak Bin</i> |
|------------------------------------------------------------------|-----------------------------|-----------------|-------------------|------------------------------------|
| total pulse<br>(PA+PB+PC+PD)                                     | Figure 10.2                 | Figure 10.3     | Figure 10.4       | Figure 10.5                        |
| outer and inner pulse<br>(PA and PB+PC+PD)                       | Figure 10.6,<br>Figure 10.7 | Figure 10.8     | Figure 10.9       | Figure 10.10                       |
| individual pulse<br>(PA, PB, PC, PD)                             | Figure 10.11                | Figure 10.12    | Figure 10.13      | Figure 10.14                       |
| individual pulse<br>(Outer (PA), lead, near, away)               | Figure 10.15                | Figure 10.16    | Figure 10.17      | Figure 10.18                       |

be referred to as an individual pulse in general or PA/PB/PC/PD pulse separately; 4) the individual pulse for the lead/near/away channel will be referred to as the lead/near/away pulse. In the first paragraph, we outline the methodology for comparing the pulse shape quantity distributions. In the second paragraph, we describe our qualitative expectations for each of the distributions.

Given that we expect both similarities and differences between the pulse shape distributions for both ‘sim’ and ‘real’ we present results in a number of ways. In some cases we will simply overlay the distributions for visual comparison so we can see similarities and differences in both range and shape. In other cases, we plot the correlation between the quantities, and where applicable for simulation, we indicate the values of the quantities as a function of radial position ( $R$ ) as an aid to identifying potential causes for the observed differences.

In general, a channel or partial combination of channels that collects more Fast Energy is expected to have a larger magnitude for *Val542*, an earlier *Peak Bin* and a higher *Peak Value*. For total pulses, all the three quantities are expected to be consistent within their respective uncertainties, based on the assumption that the total Fast Energy is basically independent of interaction position; in this case the *Peak Bin* for the total pulse is expected to be 579, as indicated from the Average

Template. For the outer and inner pulses, the three quantities are expected to exhibit a broad range of variation due to the dependence of the collected Fast Energy on  $R$ . For individual pulses, the three quantities are also expected to cover a wide range, varying with both  $R$  and angular positions, with the lead channel typically having the largest *Val542* and *Peak Value*, and the earliest *Peak Bin*.

Having described the comparison methodology and qualitative expectations, we next present the comparison results and describe the observed similarities and differences.

## **10.2 Comparison of Simulated Pulse to Real Pulse after Relative Calibration**

In this section, we compare the measured values of the three pulse shape quantities, *Val542*, *Peak Bin* and *Peak Value*, between ‘sim’ and ‘real’ across the channel configurations given in Table 10.1. On the one hand, the simulations generally follow the expectations, and the comparisons show qualitative agreement, with many of their distributions exhibiting similar shapes. On the other hand, quantitative differences are clearly evident, as the values of the average (mean) and root mean square (RMS) of their distributions can show significant variation. While the causes of these differences are not yet fully understood, and will be the subjects of future work, some of them appear to be as simple as timing effects in the simulation, but others are far from clear. Given that we have truth information, preliminary studies indicate that many are correlated with the interaction positions, so we will present what we believe are the most relevant facts we do have. In Section 10.2.1, we present a series of comparisons of between ‘sim’ and ‘real’ pulse distributions. In Section 10.2.2, we summarize the similarities and differences. We note that we present some of the hypotheses to potentially explain the differences in the next section.

### **10.2.1 Results of Comparison**

In this subsection, we provide detail on the similarities and differences between ‘sim’ and ‘real’ across the pulse shape distributions. For each set of comparisons we start by looking at the one-dimensional distributions for qualitative agreement. As part of the process, in some cases we plot the correlation between quantities, and where applicable for simulation indicate the quantities as a function of position as an aid to identifying potential causes for the observed differences; we

note in advance that the biggest differences occur for  $R > 25$  mm, which we will refer to as large  $R$ . Since there are many differences, we present the data in an systematic way in this subsection, and draw conclusions in the next. In the first paragraph, we compare the pulse shape quantity results for total pulses. In the second paragraph, we compare the pulse shape quantity results for the outer and inner pulses. In the third paragraph, we compare the pulse shape quantity results for individual pulses in terms of PA, PB, PC, and PD. In the fourth paragraph, we compare the pulse quantity results for individual pulses in terms of the lead, near, and away.

The comparison for total pulses are shown in Figures 10.2 - 10.5. Given that the phonon energy has to arrive somewhere and is nominally collected in the same way over time, independent of interaction position, we expect only Gaussian variation around the mean of each. As expected, the one-dimensional distributions for ‘real’ exhibit Gaussian variation for all three pulse shape quantities. On the other hand, for ‘sim’, the distribution of *Peak Bin* looks fairly Gaussian but is shifted to earlier times than for ‘real’, while the distributions of *Val542* and *Peak Value* are not Gaussian-like. Of further note is that in simulation both *Peak Bin* and *Peak Value* are correlated with  $R$ , as visualized in Figure 10.5, with the biggest differences occurring for  $R > 25$  mm.

The comparison for outer and inner pulses are shown in Figures 10.6 - 10.10. Given that the sharing of Fast Energy between the inner and outer channels varies as a function of  $R$ , we expect both significant variation in each as well as correlated values of the pulse shape quantities. We observe this type of variation in both ‘sim’ and ‘real’, but there is much bigger variation in the results for ‘sim’, although there is an overlapping portion with ‘real’. Again, for simulation where we have truth position, we see qualitative agreement with expectations as a function of  $R$ , but that the biggest differences are for the largest values of  $R$ .

The comparison for individual pulses, in terms of PA, PB, PC, and PD, are shown in Figures 10.11 - 10.14. Given that the amount of Fast Energy collected by each channel varies significantly with the interaction position, we again expect the distribution of each quantity to expand to wide ranges and be correlated between channels. In addition, due to the symmetric layout of PB/PC/PD and the ring-shaped PA, we further expect the distributions to be consistent between

the former, but different for the latter. We observe these for both ‘sim’ and ‘real’. As observed in the comparisons above, the distributions for ‘sim’ are wider than ‘real’. We find that, while the distributions of *Peak Value* vs. *Peak Bin* for PB/PC/PD appear to have L-shapes for both ‘sim’ and ‘real’, a number of events in ‘sim’ are away from the shape, and that they occur for large  $R$ .

The comparison for individual pulses, in terms of lead, near, and away, are shown in Figures 10.15 - 10.18. This comparison highlights the similarities and differences described in the previous paragraph based on the sharing of Fast Energy among the three inner channels. We point out that the deviation in ‘sim’ from ‘real’ are again mostly from events with large  $R$ .

Having presented the comparisons between ‘sim’ and ‘real’ data, we next summarize the findings and conclude.

### 10.2.2 Summary of Comparison

In this subsection, we summarize the similarities and differences that we find in the comparisons between ‘sim’ and ‘real’ and expectations as well as what we can potentially infer from the truth positions in simulation. In the first paragraph, we summarize the similarities. In the second paragraph, we summarize the differences.

Both the ‘sim’ and ‘real’ show qualitative agreement with the expectations from the two-circle model in which the Fast Energy sharing has positional variation especially as a function of  $R$  as indicated by the simulations. Many of the distributions show similar means, and some show similar correlations between quantities and follow the expectations as a function of  $R$ . We observe that the variation in the distributions, as expected, becomes larger as we consider smaller slices of the collection region such as individual channels and combined inner channels.

In all cases the ‘sim’ results show significant quantitative differences from ‘real’. For total pulse comparison, there is an unexpected non-Gaussian variation for some of the distributions for ‘sim’. While we do not have truth position quantities for real data, we see that the systematic differences in ‘sim’ appear to be  $R$  dependent. For smaller slices of channels (combined inner channels and individual channels), the differences between ‘sim’ and ‘real’ become more pronounced. The results from events in ‘sim’ with  $R > 25$  mm are most different from ‘real’. On the other hand, there still

are differences but they are more limited to shifts of the means and ranges of their distributions.

With the summary of the comparison complete, we describe several hypotheses to potentially explain the trends observed in differences.

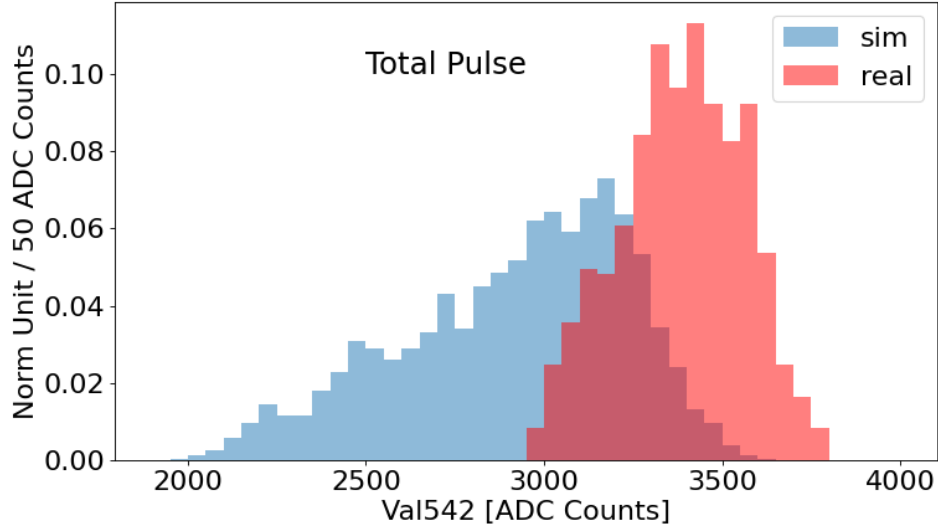


Figure 10.2: This figure shows the distributions of *Val542* for the total pulses in both simulated pulses, ‘sim’ (blue), and real pulses after relative calibration, ‘real’ (red). We show it because *Val542* for total pulses is expected to be consistent across all events, given the selection of single-energy events and relative calibration, with variations arising only from measurement resolution. The distribution for ‘real’ is primarily Gaussian, as expected, whereas that for ‘sim’ has a larger RMS and smaller mean, as well as an asymmetry towards lower values.

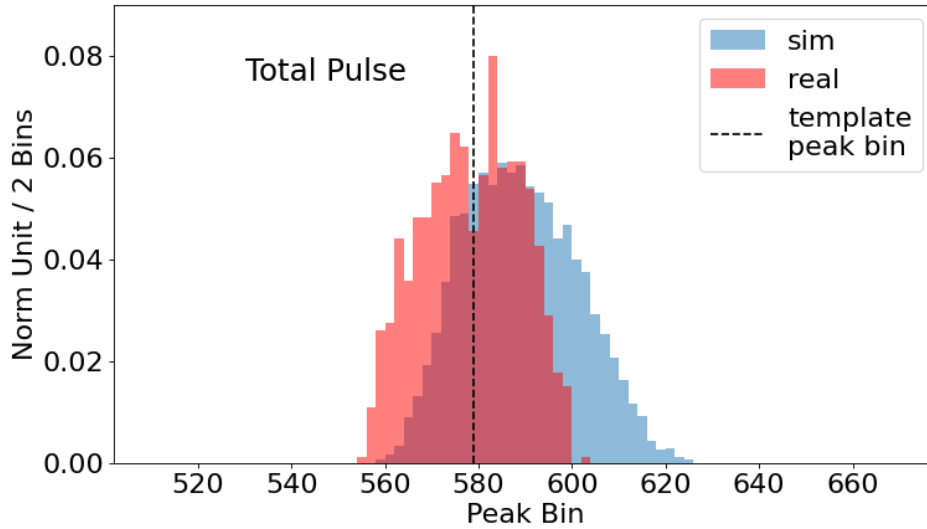


Figure 10.3: This figure shows the same events and format as Figure 10.2 but for *Peak Bin*, including the expectation from the Average Template (dashed line). Similarly, we show it because *Peak Bin* for total pulses is expected to be consistent across all events. The *Peak Bin* distributions for both ‘sim’ and ‘real’ are approximately Gaussian. However, the ‘real’ aligns well with the expectation from the Average Template shown in Figure 8.1, whereas the ‘sim’ exhibit a slightly delayed *Peak Bin* of about 10 bins. Further analysis is provided in Figure 10.5.

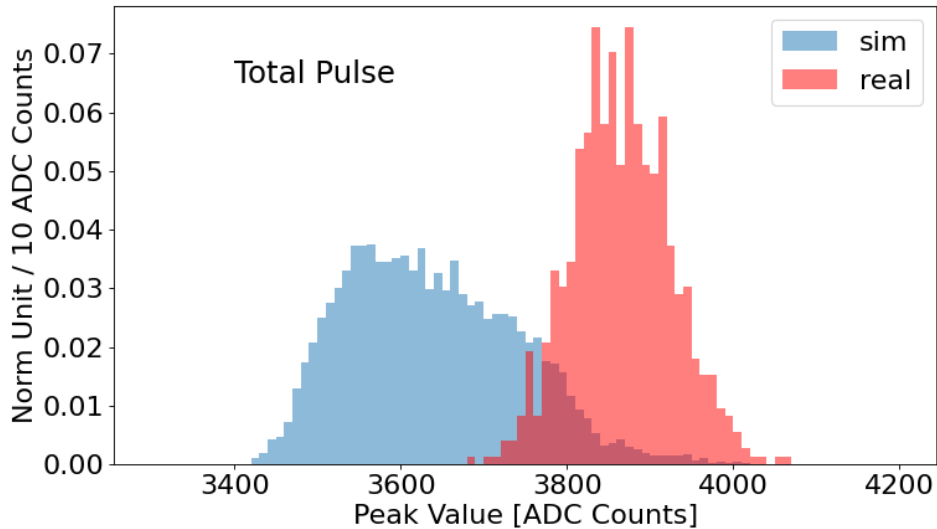


Figure 10.4: This figure shows the same events and format as Figures 10.2 and 10.3 but for *Peak Value*. Similarly, we show it because *Peak Value* for total pulses are expected to be consistent across all events. The distribution for ‘real’ is primarily Gaussian, in line with expectations, while that for ‘sim’ has a larger RMS as well as a smaller mean and an asymmetry toward higher values. Further analysis is provided in Figure 10.5.

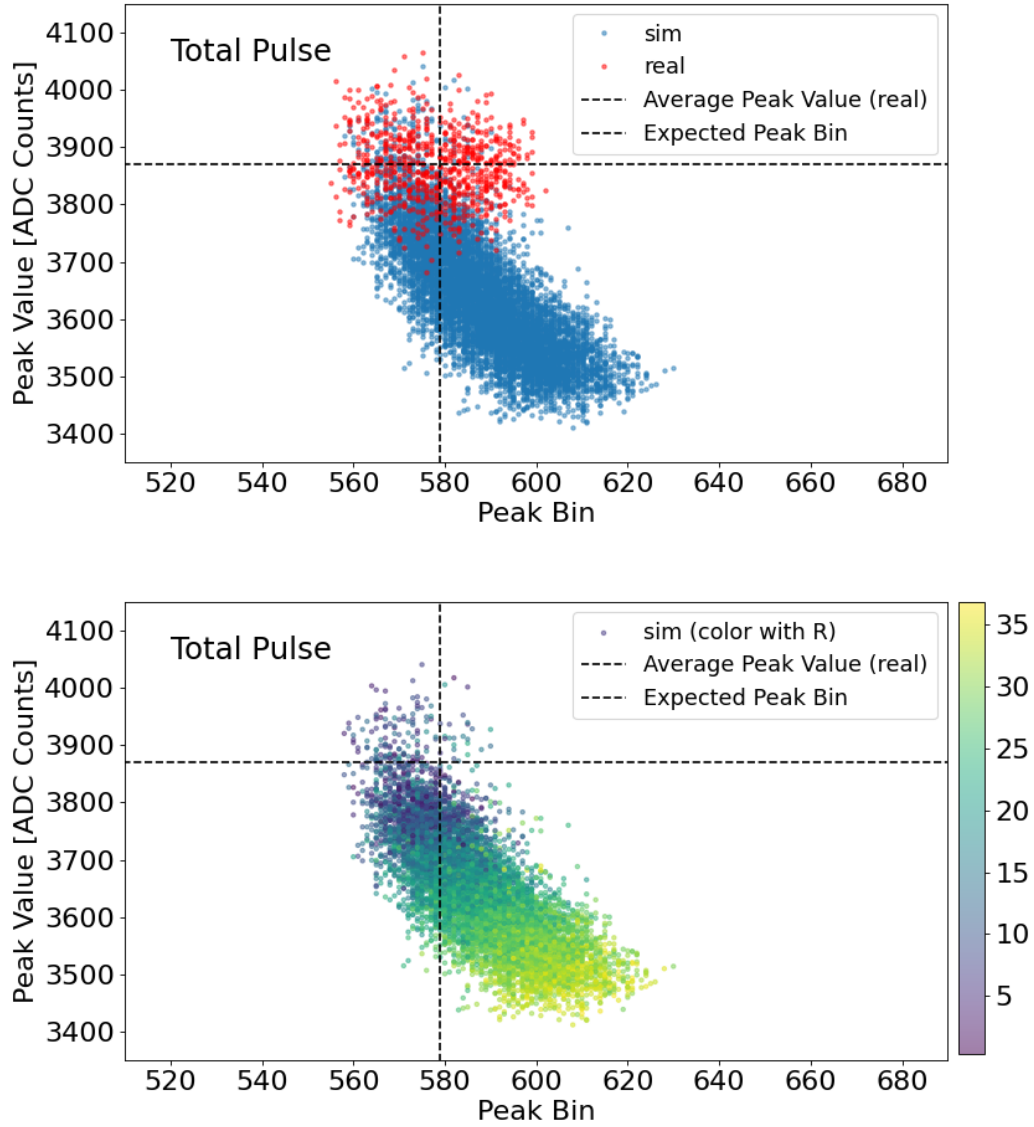


Figure 10.5: This figure shows two versions of the correlation between *Peak Value* and *Peak Bin* for total pulses. We show it to highlight that these two quantities appear uncorrelated in ‘real’, but are very correlated in ‘sim’. The bottom plot shows ‘sim’-only but with the individual events color coded by  $R$  (purple/blue for smaller  $R$  and green/yellow for larger  $R$ ). Both quantities in ‘sim’ exhibit a clear correlation as a function of  $R$  and the biggest differences are for the largest values of  $R$ .



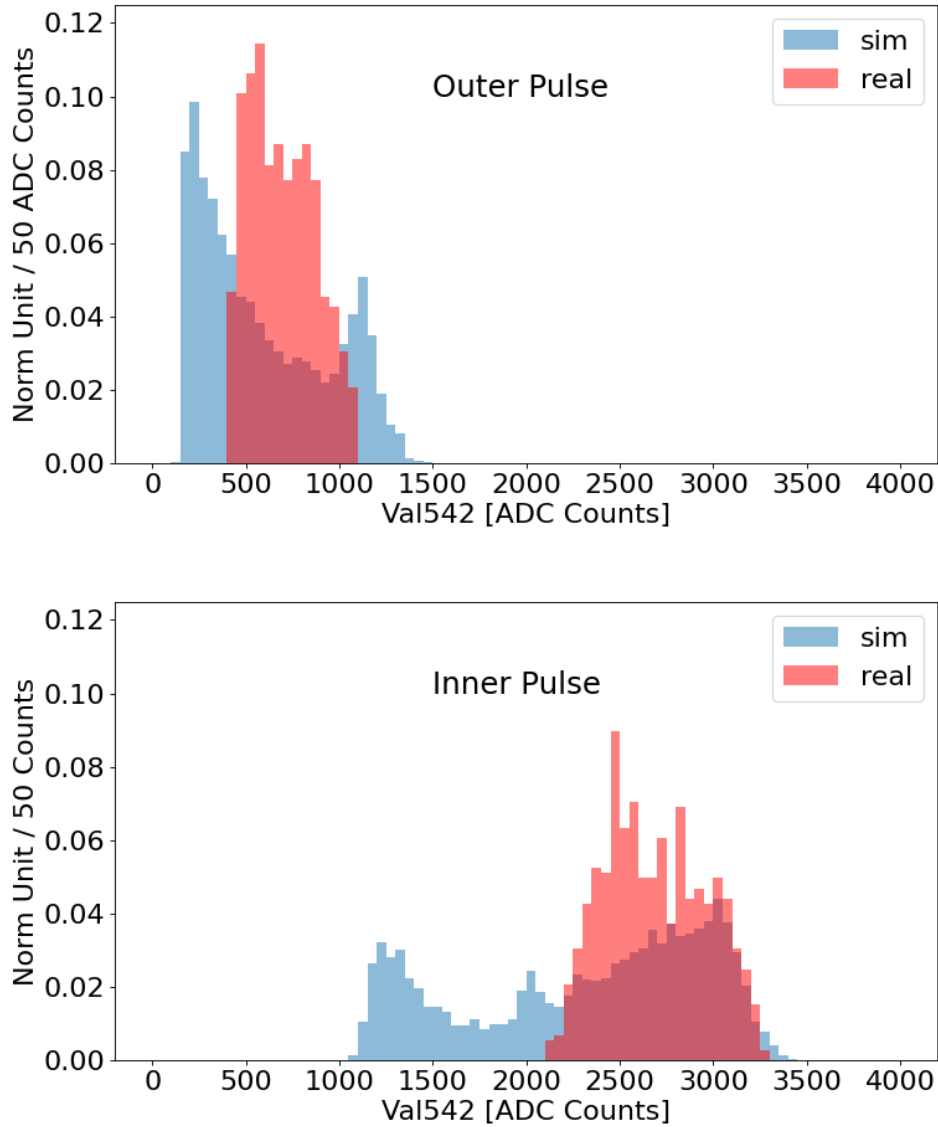


Figure 10.6: This figure shows the distributions of *Val542* for the outer and inner pulses in both ‘sim’ and ‘real’. We show it because *Val542* values are expected to differ between the outer and inner pulses, due to varying amounts of Fast Energy collected. The ‘sim’ distribution is notably broader than ‘real,’ for both distributions, as well as having very different shapes. Further analysis is provided in Figure 10.7.

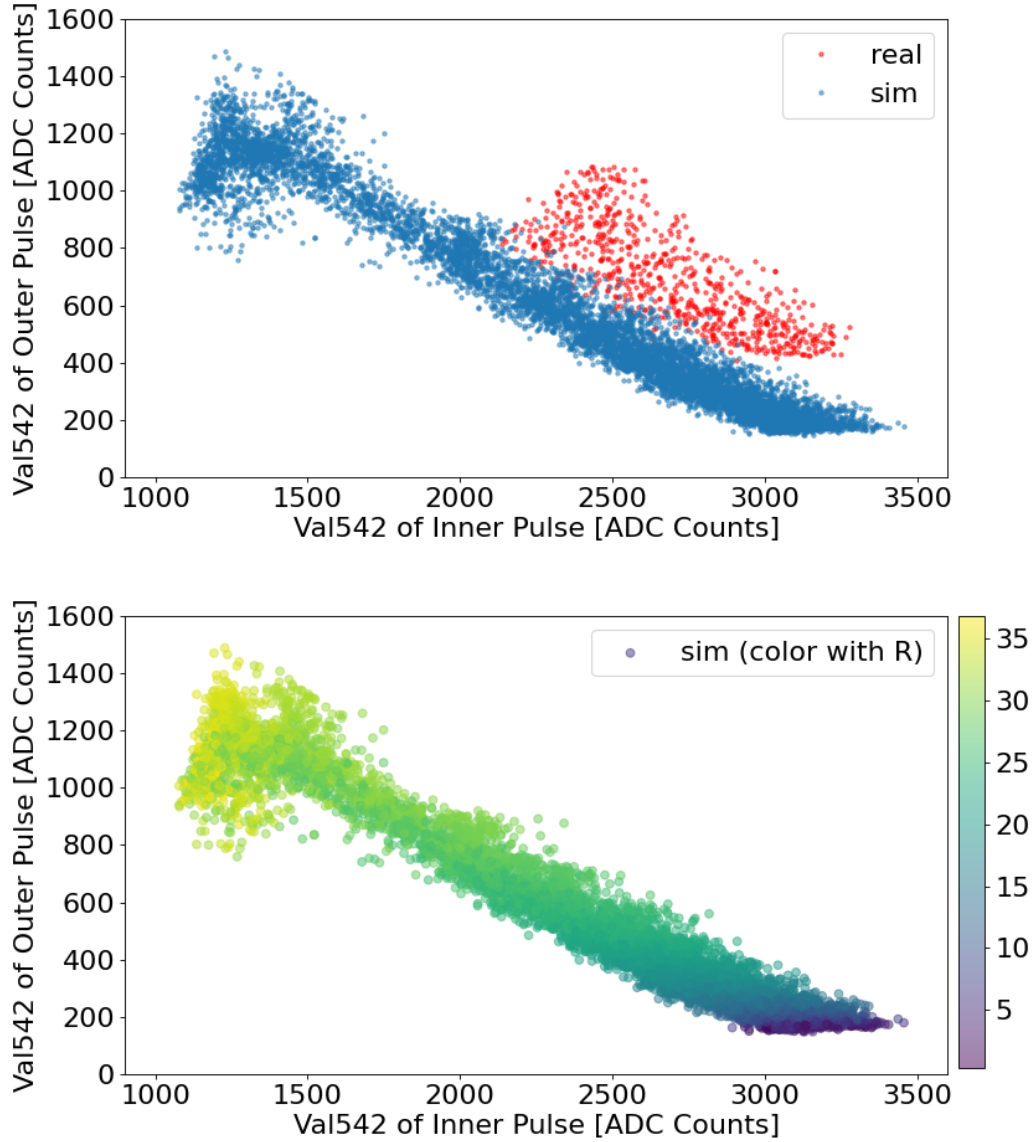


Figure 10.7: This figure shows two versions of *Val542* for the outer vs. inner pulses in both ‘sim’ and ‘real’ as shown in Figure 10.6 but using the format of Figure 10.5. We show it to illustrate similarities and differences between ‘sim’ and ‘real’, as well as the correlation’s dependence on  $R$  in simulation. In the top plot, both ‘sim’ and ‘real’ exhibit a similar trend, qualitatively consistent with the expected distribution of Fast Energy between the outer and summed inner channels as shown in Figure 3.13. However, ‘real’ shows an overall higher distribution compared to ‘sim.’ The bottom plot shows that the correlation between *Val542* for the outer and inner pulses is also a strong function of  $R$  with the biggest differences between ‘real’ and ‘sim’ occurring for the largest values of  $R$ .

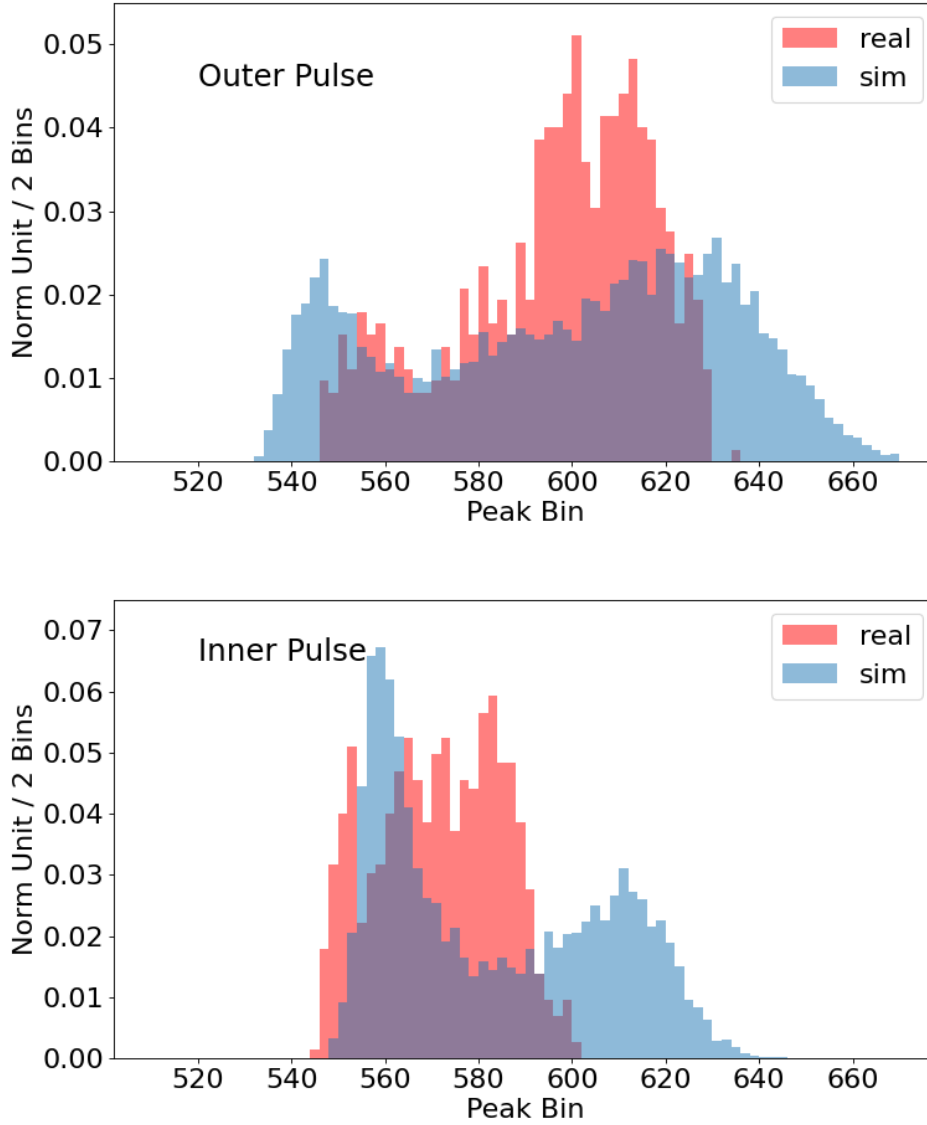


Figure 10.8: This figure shows the same events and format as Figure 10.6 but for *Peak Bin*. We show it because *Peak Bin* is expected to differ between the outer and inner pulses as it is affected by the varying amounts of Fast Energy collected. The ‘sim’ distributions are notably broader than ‘real’ and double-bumped, with further analysis provided in Figure 10.10.

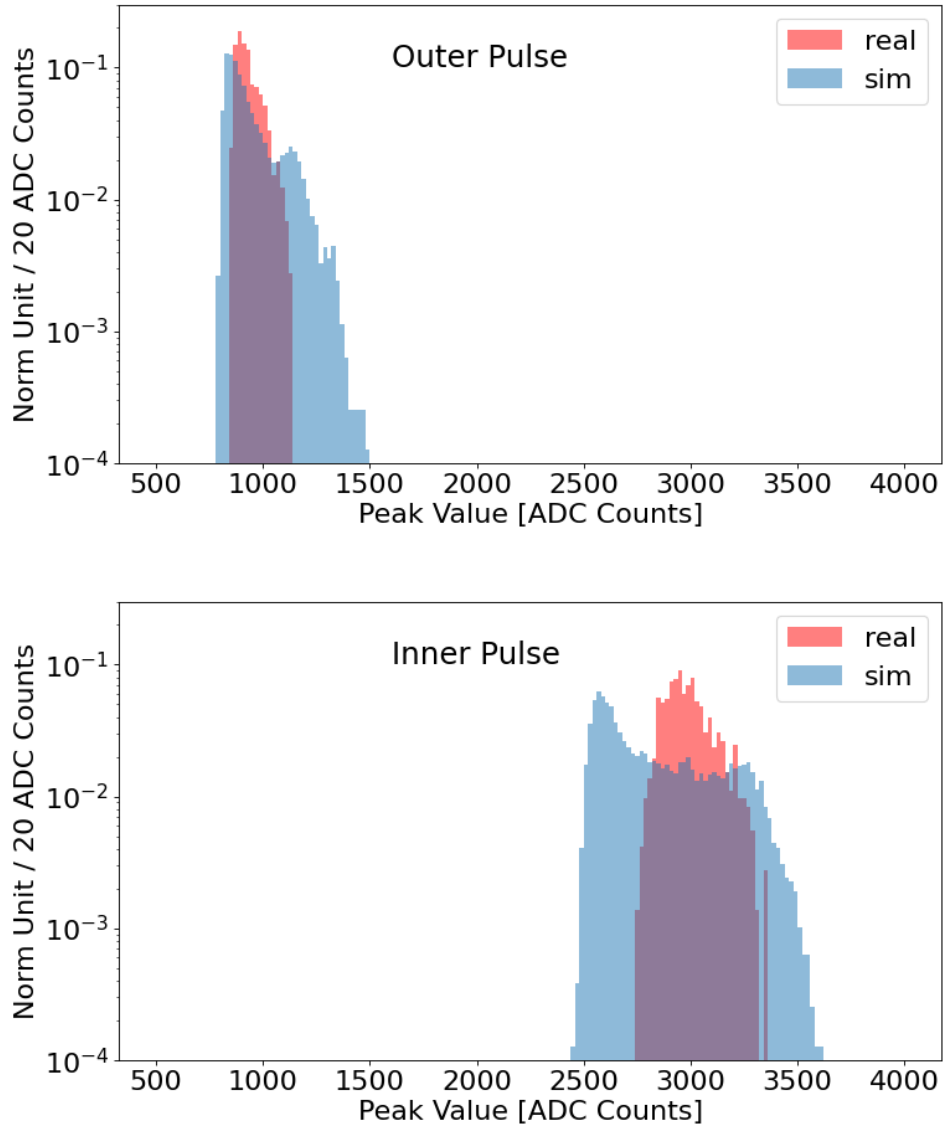


Figure 10.9: This figure shows the same events and format as Figures 10.6 and 10.8 but for *Peak Value*. We show it because *Peak Value* is expected to differ between the outer and inner pulses due to the varying amounts of Fast Energy collected. The ‘sim’ distribution is notably broader than ‘real’ and double-bumped, with further analysis provided in Figure 10.10.

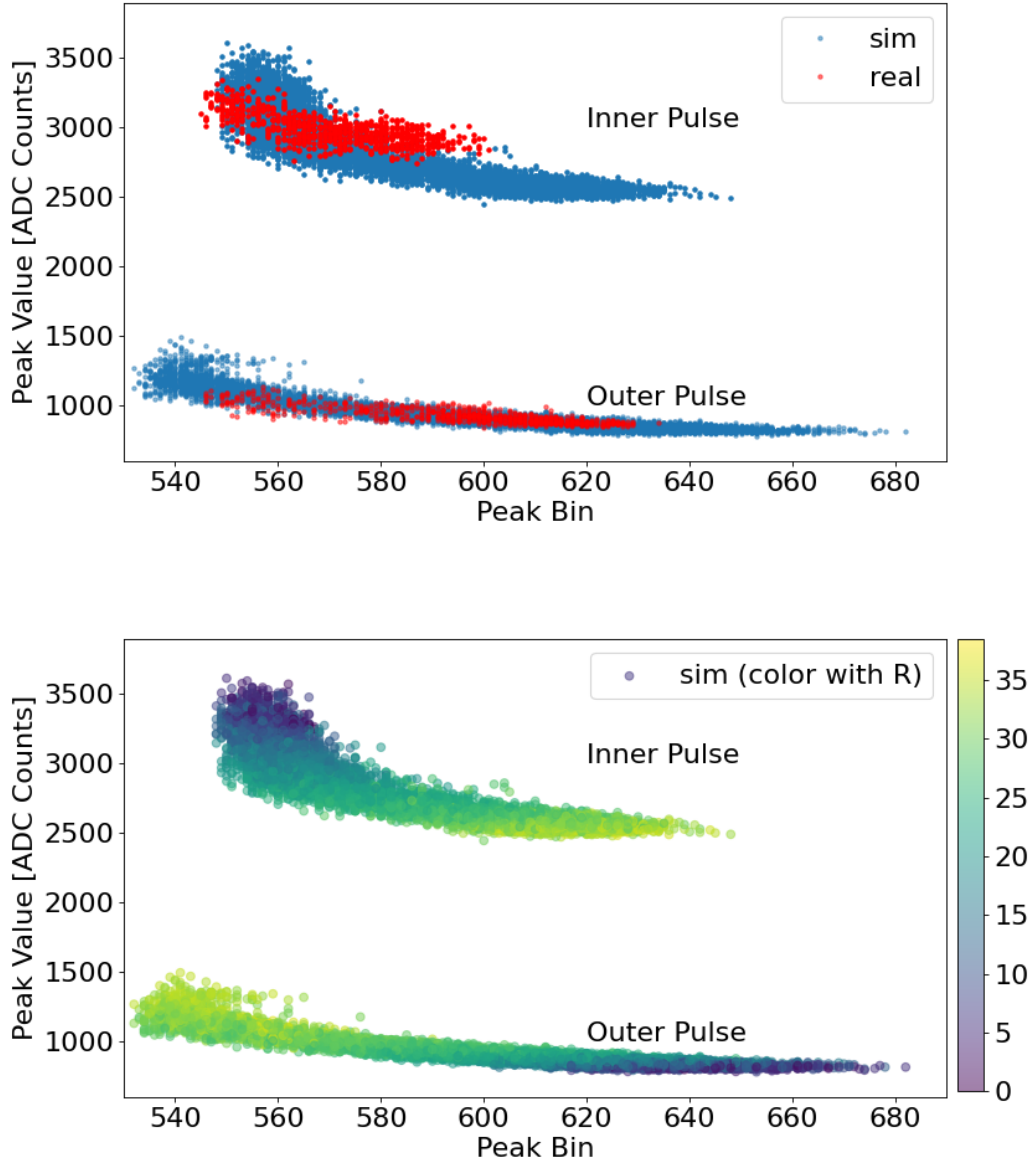


Figure 10.10: This figure shows two versions of *Peak Value* vs. *Peak Bin* for the outer and inner pulses in both ‘sim’ and ‘real’ as shown in Figures 10.8 and 10.9 but using the format of Figure 10.5. We show it to illustrate similarities and differences between ‘sim’ and ‘real’, as well as the correlation’s dependence on  $R$  in simulation. In the top plot, both ‘sim’ and ‘real’ have overlapping distributions and exhibit the similar trend that *Peak Value* decreases as a function of *Peak Bin*. However, in both cases, the ‘sim’ distribution is wider than the ‘real.’ The bottom plot shows the same results but by color coding for each event for ‘sim’-only, and reveals the same trends: the correlation between *Peak Value* and *Peak Bin* varies significantly with  $R$  for both the outer and inner pulses.

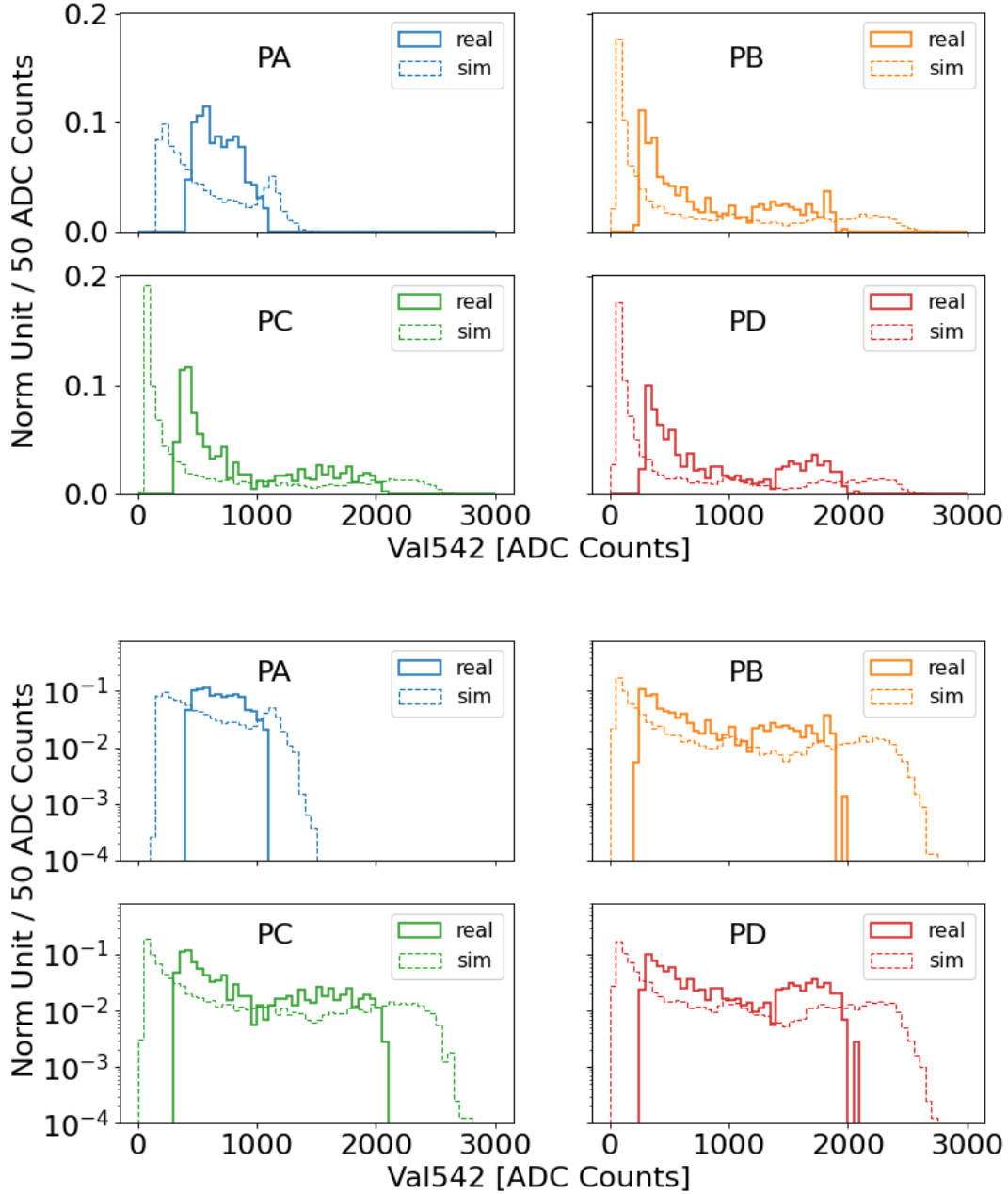


Figure 10.11: This figure shows two versions of the distributions of *Val542* for individual pulses in both ‘sim’ and ‘real’ in terms of PA, PB, PC, and PD. We note the formatting has changed from earlier figures such that here ‘sim’ is indicated with solid lines and ‘real’ is indicated with dashed lines, and PA, PB, PC, and PD channels are indicated in blue, yellow, green, and red, respectively. We show it because *Val542* is expected to vary across channels due to different amounts of Fast Energy collected. The top set of plots uses a linear y-scale, while the bottom uses a logarithmic y-scale, providing a clearer comparison of different distribution details. On the one hand, PB, PC and PD have the same distribution shape, as expected from their symmetric layout, and a slightly double-bumped structure; while PA has a different distribution as it has a ring-like shape, we note that ‘real’ appears single bumped, but the ‘sim’ is double-bumped. We also note that again the ‘sim’ distributions are all broader than ‘real’.

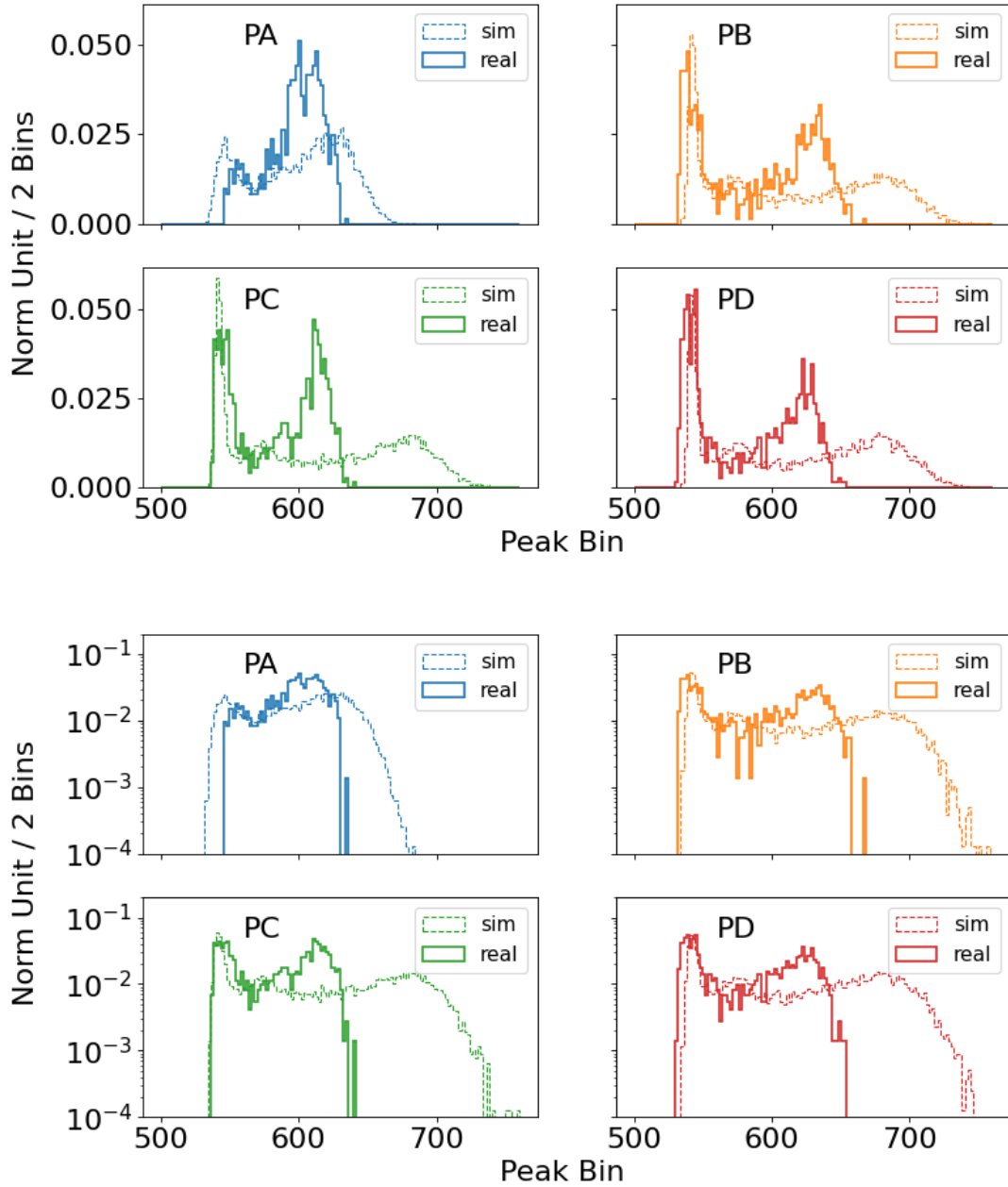


Figure 10.12: This figure shows the same set of plots as Figure 10.11 but for *Peak Bin*. We show it because *Peak Bin* is expected to vary across channels as it is affected by the varying amounts of Fast Energy collected. The shapes of the ‘sim’ distributions resemble the ‘real’ distributions in some ways, but are notably broader, with further analysis provided in Figure 10.14.

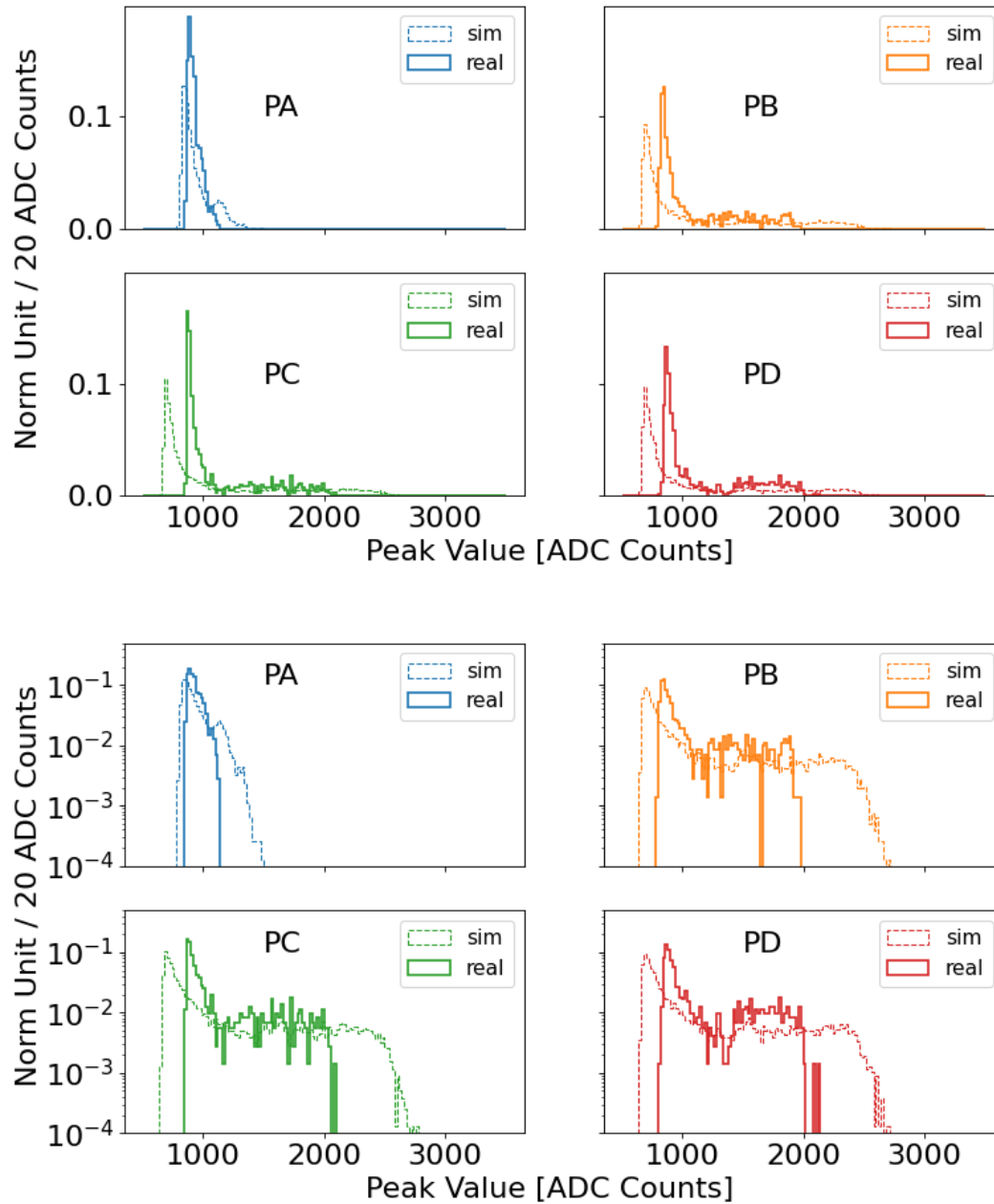


Figure 10.13: This figure shows the same set of plots as Figures 10.11 and 10.12 but for *Peak Value*. We show it because *Peak Value* is expected to vary across channels as it is affected by the varying amounts of Fast Energy collected. Again, the ‘sim’ distributions resemble the ‘real’ distributions in general but are notably broader and PA shows a double peak. Further analysis is provided in Figure 10.14.



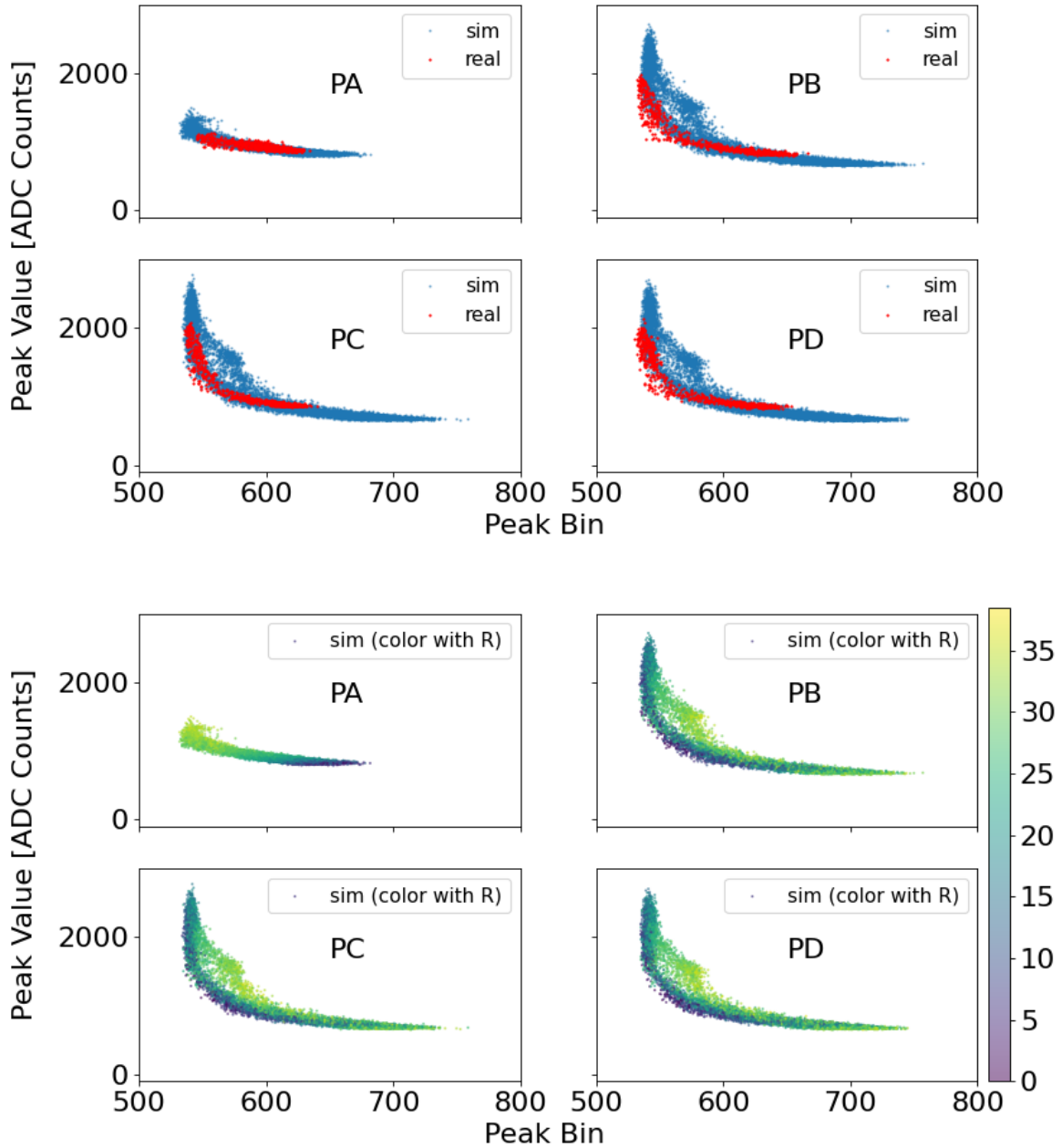


Figure 10.14: This figure shows two versions of *Peak Value* vs. *Peak Bin* for the four individual channels in both ‘sim’ and ‘real’ as shown in Figures 10.12 and 10.13 but using the format of Figure 10.5. We show it to highlight similarities and differences between ‘sim’ and ‘real’, as well as the correlation’s dependence on  $R$  in simulation. In the top set of plots, ‘sim’ exhibits the same L-shaped distribution as ‘real’ but with broader distributions and an additional group of points outside the L-shape for the PB, PC, and PD channels. The bottom set of plots shows ‘sim’-only, revealing that the major discrepancies between ‘sim’ and ‘real’ occurs for large  $R$ .

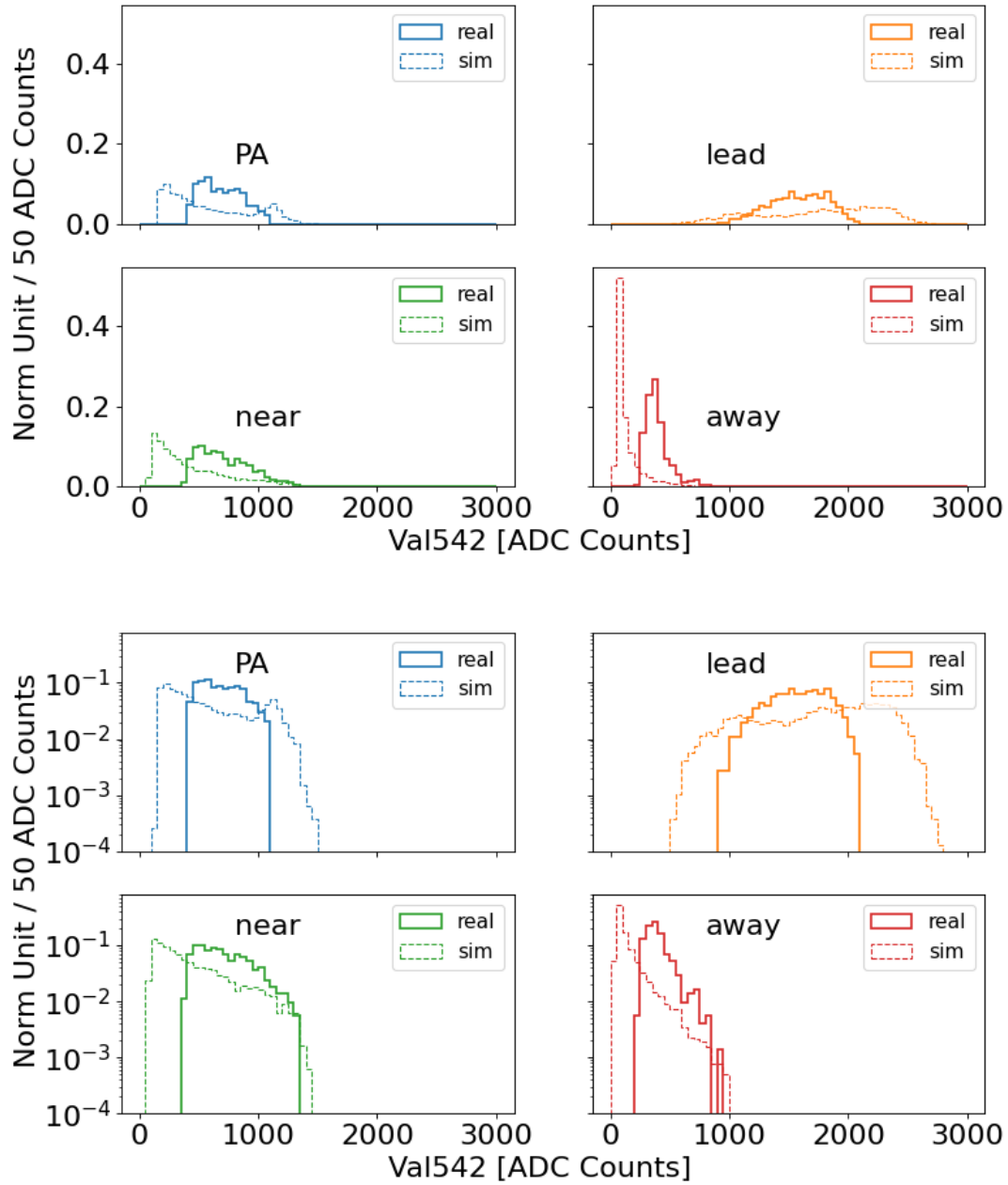


Figure 10.15: This figure shows the same set of plots of *Val542* as in Figure 10.11 but organized by PA, lead, near, and away channels. We show it because *Val542* is expected to vary across channels due to different amounts of Fast Energy collected. Among the three inner channels, the lead channel has the largest *Val542*, as it collects the most Fast Energy by definition, while the near and away channels have smaller values due to collecting less Fast Energy. The shapes of the ‘sim’ distributions resemble the ‘real’ distributions in some ways, but are notably broader.

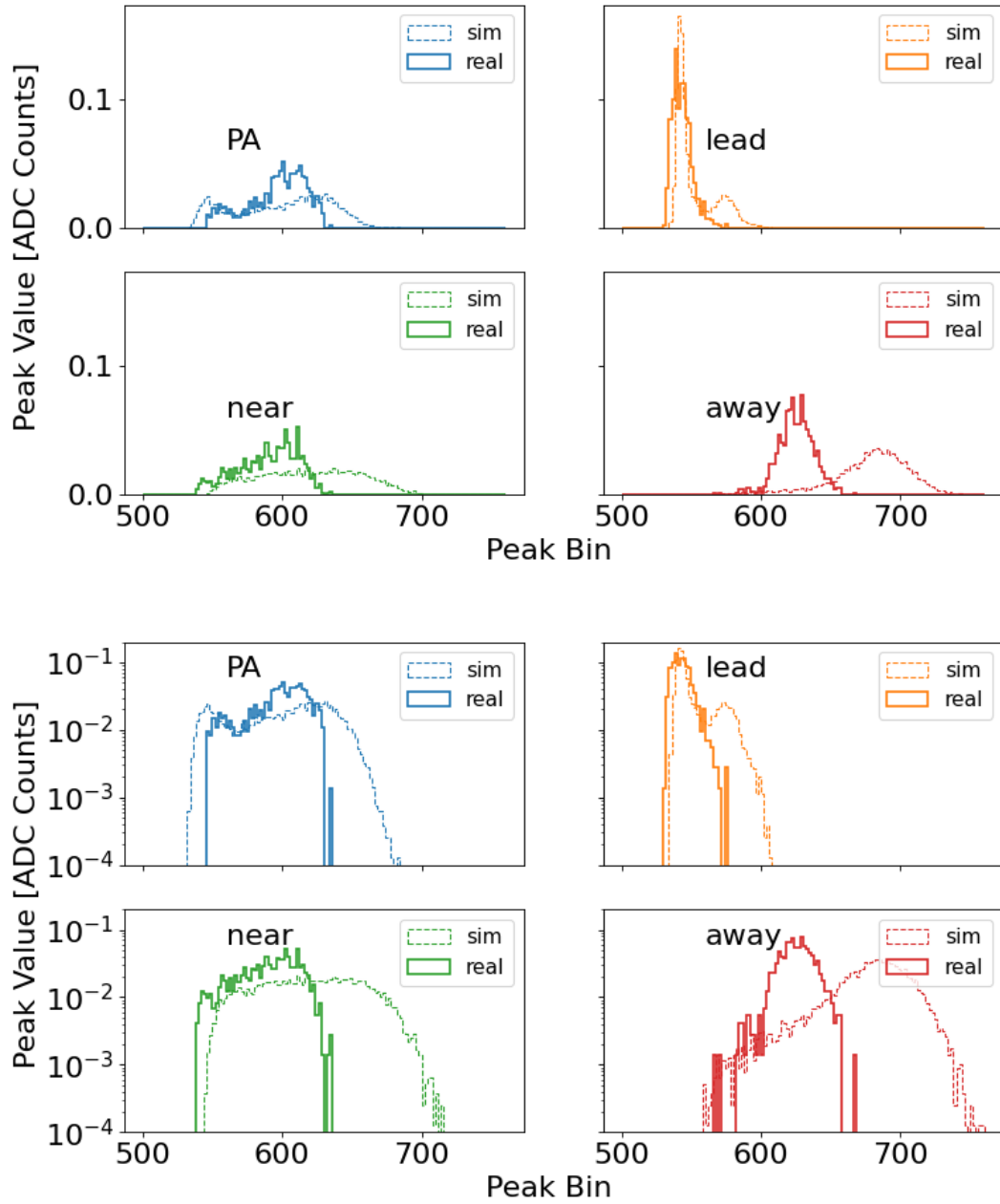


Figure 10.16: This figure shows the same set of plots as Figure 10.15 but for *Peak Bin*. We show it because *Peak Bin* is expected to vary across channels as it is affected by the varying amounts of Fast Energy collected. As expected, among the three inner channels, the lead channel has the earliest *Peak Bin*, as it collects the most Fast Energy, while the near and away channels have later *Peak Bin* due to collecting less Fast Energy. While we observe the same pattern of ‘sim’ being wider than ‘real’, we also note that the lead channel in ‘sim’ has a second peak that ‘real’ does not. Further analysis is provided in Figure 10.18.

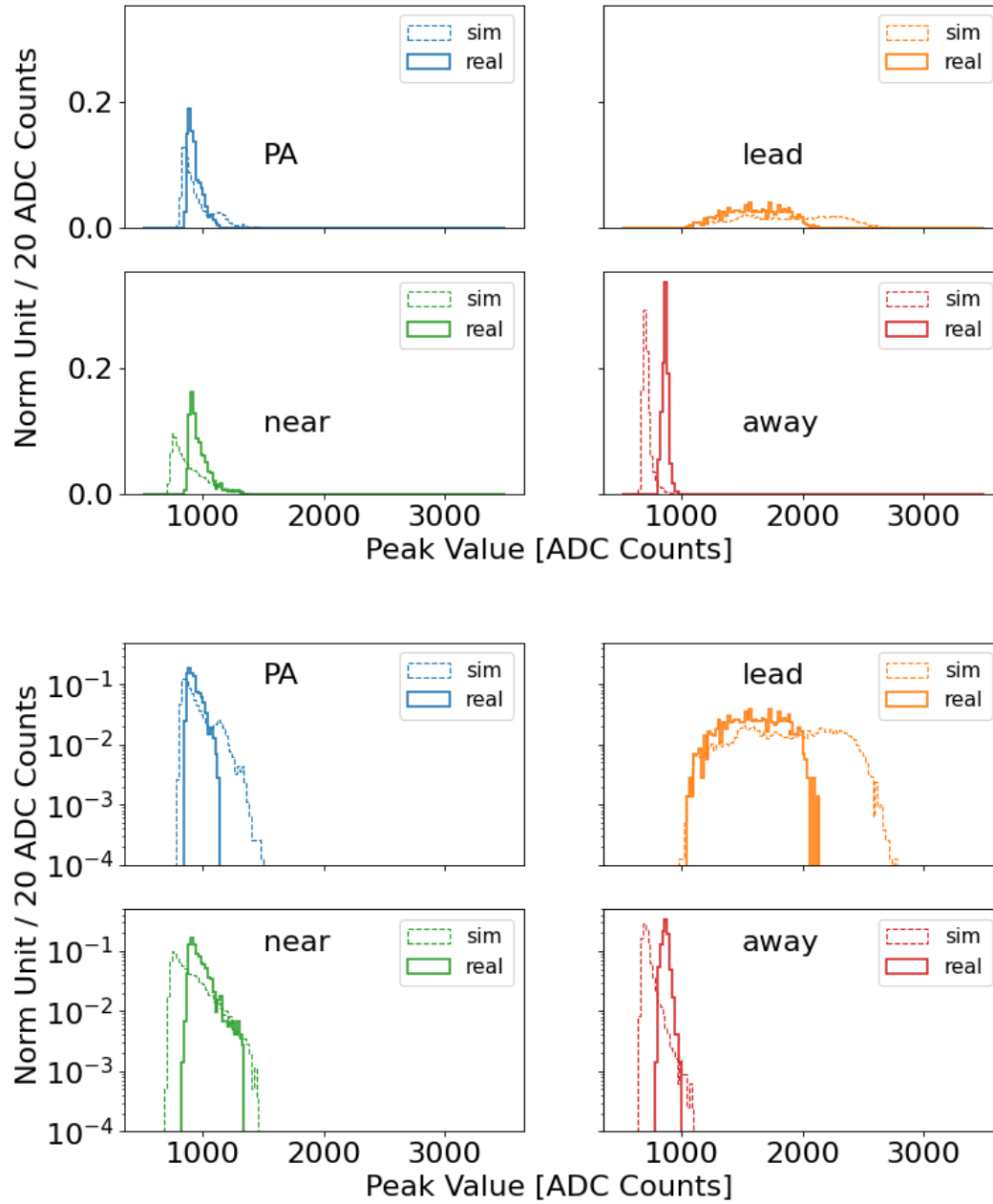


Figure 10.17: This figure shows the same set of plots as Figures 10.15 and 10.16 but for *Peak Value*. We show it because *Peak Value* is expected to vary across channels as it is affected by the varying amounts of Fast Energy collected. As expected, among the three inner channels, the lead channel has the largest *Peak Value*, as it collects the most Fast Energy, while the near and away channels have less *Peak Value* due to collecting less Fast Energy. Comparing to Figure 10.16, we see similar trends in the differences between ‘real’ and ‘sim’. Further analysis is provided in Figure 10.18.

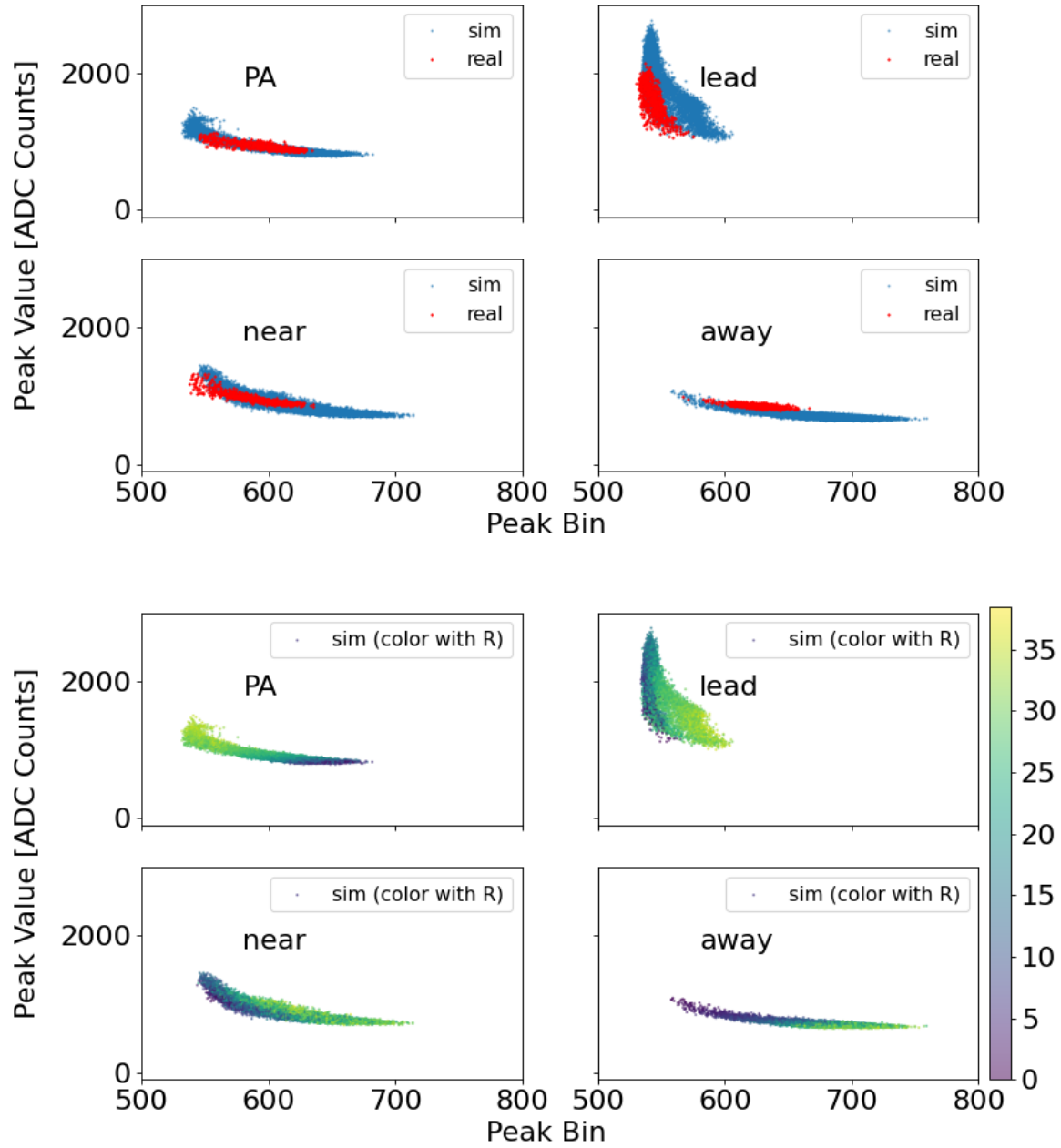


Figure 10.18: This figure shows the same set of plots as Figure 10.14 but organized by PA, lead, near, and away channels. We show it to highlight similarities and differences from another perspective. In the top plot, we see that the L-shaped distributions shown in Figure 10.14 splits into three parts for both ‘sim’ and ‘real’. In the bottom plot we see again that major discrepancies between ‘sim’ and ‘real’ occur for large  $R$ .

### 10.3 Hypotheses to Potentially Explain the Differences between Simulated and Real Data

In this section, we describe several preliminary hypotheses as our first attempts to explain the differences observed in our comparisons. The trends in the differences, overall shifts in values as well as even more pronounced differences for large  $R$ , indicate that there are gaps between the understanding we have put in the simulation about the dominant microphysical process and the observations in the real experiment, leaving challenges to be solved. We consider problems in the assumptions in the data analysis as well as in the microphysics modeled in simulation. There is a good chance there are multiple issues, some of which obscure others. In the first paragraph, we describe how the use of differing event selection methods for the simulated and real datasets might explain some of the differences. In the second paragraph, we comment on the possible mismodeling of phonon reflection in simulation, which might result in the observed differences, especially most pronounced for large  $R$ . In the third paragraph, we comment on the possibility that the differences in the means of many of the time-related distributions could be explained by a simple timing shift in the simulation. In the fourth paragraph, we describe the potential influence of charge transport dynamics on the observed differences.

The use of differing event selection methods for the simulated and real datasets might explain some of the differences. For simulated data, well-measured events were selected based on the observation that their distribution have a fairly narrow value of the collection efficiency, as shown in Figure 6.2. For real data, the selection uses the peak of the PTNFamps distribution, as shown in Figure 4.5, which we assume is functionally equivalent to that applied in simulation, both in terms of maintaining the sample purity and in avoiding a systematic bias against certain types of events. In principle, there is good reason to believe that the different selection criteria should allow for an apples-to-apples comparison. However, the results from simulation suggest that, when a real event occurs for large  $R$ , the total pulse may have both a later *Peak Bin* and a smaller *Peak Value*. As a result, when processed by the OF algorithm with non-stationary noise, such an event can yield a PTNFamps value that is smaller than the acceptance window for well-measured events. In other words, the selection criteria applied to the real data may exclude a portion of the events where all the

Luke phonon energy was collected, but it was rejected because it didn't have the 'right' shape. On the other hand, if the events were systematically mismeasured we would see a lot more events below the peak in real data, which is not observed, and events from photons from the cavern are expected in that region, and show up at higher energies as well. We note that there may be other reasons that those large  $R$  events were removed, or never included/created in the first place, for example if the assumption that the Ge-71 activations are uniformly distributed is erroneous as suggested in Ref. [39].

A reasonable hypothesis to explain that the most pronounced differences occurring for large  $R$  is that the phonon reflections in simulation may be improperly modeled. The version of the simulation used to make the samples for this work employs a purely diffuse phonon reflection model, where phonons are scattered in random directions upon hitting a detector edge. This may inaccurately represent real phonon propagation near the sidewall as there is no substantive data on these processes. Since, at the time of this analysis, the simulations could not perform specular reflection, we have used a toy detector model to conduct a simple preliminary study comparing the phonon energy collected by an inner channel under different reflection assumptions. Essentially, the amount of Fast Energy in Figure 3.13 that would have gone outside the circle for large values of  $R$  was placed as Slow Energy for a fully diffuse configuration, while in a specular configuration it was folded back into the Fast Energy. The top subfigure of Figure 10.19 establishes a baseline using the original Fast Energy distribution based on the purely diffuse reflection model, while the bottom one shows the results obtained with a modified distribution emulating purely specular reflection. The noticeable difference between the resulting energy profiles suggests that the type of reflections influences the distributions, and may account for all or part of the observed differences. For events for large  $R$ , this is expected to impact a larger fraction of the phonons produced along the charge trajectories as they are created near the sidewall and thus more likely to have an early reflection. On the other hand, phonons with multiple reflections are expected to arrive much later in time and so it is not clear how that could be the cause of the different peak quantity distributions.

Another reasonable hypothesis that might explain the differences in the means of many of the

time-related distributions is that there is a simple timing shift in the simulation. This difference is most cleanly observed in Figure 10.3. As described in Section 2.3, the readout of events in the data by the DAQ is designed such that there is a pre-pulse region that is expected to be pure noise that precedes the actual interaction signal. In particular, the filtering algorithms of the trigger during readout are designed to make the length of the pre-pulse region always be the same for all events. We hypothesize that the timing configuration in the simulation, which always places the start of an event at the same time, differs from that of the real-world electronics, resulting in a systematically later *Peak Bin* in the simulated data than in the real data. To test this, Figure 10.20 shows a zoomed-in version of the pulse start times where such a shift could be seen most readily. We see that the example simulated total pulse begins to rise approximately 10 bins ( $16\ \mu\text{s}$ ) later than the Average Template, which is consistent with the results shown in Figure 10.3. We note that this problem has been fixed in versions of DAQSim that were developed after this result, and appears to account for many of the differences in the shifted means of the *Peak Bin* and *Val542* distributions.

A final hypothesis we note that might explain some of the differences is that a fully quantum mechanical modeling of the charge transport dynamics was introduced to G4CMP only after these samples were created. The germanium crystal lattice provides a periodic potential within the detector for the charges, and this potential is anisotropic around the atoms [52]. This causes electrons to propagate with direction-dependent velocities, and their acceleration is governed not only by external forces but also by the crystal orientation. Additionally, electrons undergo scattering from the lattice and other particles. While early versions of the complex modeling of these effects were present in the version of G4CMP used to make the samples, we now know that the parameterizations and parameter values did not fully or accurately represent the physical processes in the real world, which could explain some of the remaining differences between the ‘sim’ and ‘real’. Work on this is in progress [53].

Having completed the discussion of a set of hypotheses that could potentially explain the differences between ‘sim’ and ‘real’, in the next and last chapter, we outline future work based on this study and conclude the thesis.



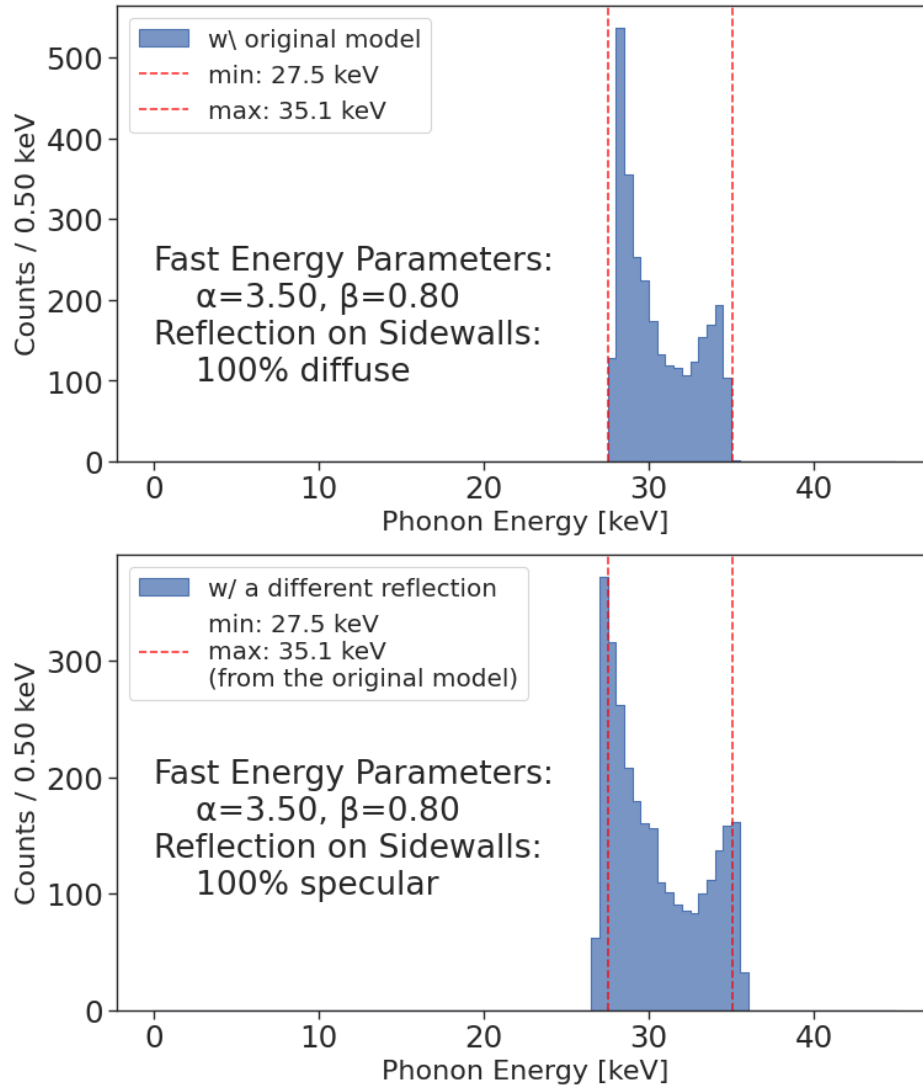


Figure 10.19: This figure compares two distributions of the phonon energy collected by an inner channel under two reflection models: purely diffuse (top) and purely specular (bottom), using a simple fast parameterization model based on the results from Section 7.3. We show them to illustrate effects from the different reflection models on energy collection as a potential hypothesis to explain the existing difference between simulated and real pulses. The top plot, based on the 100% diffuse reflection model (currently assumed in G4CMP), spans an energy range of 27.5–35.1 keV and serves as the baseline for comparison. The bottom plot is identical in setup except that the reflection model is changed to 100% specular reflection at the sidewalls. While the broader distribution of the phonon energy under the specular reflection model provides preliminary insight into how reflection behavior may contribute to the differences discussed in the previous section, it is not clear how reflections would affect the peak quantity distributions.

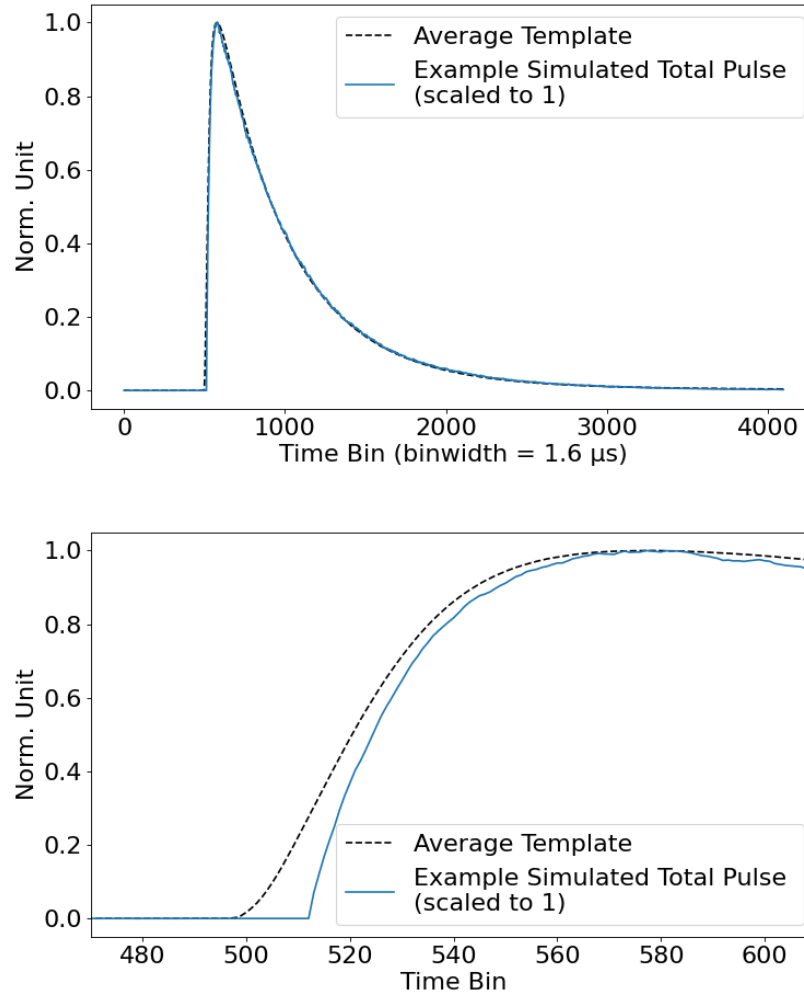


Figure 10.20: This figure shows two comparisons of a single example simulated total pulse along with the Average Template. We show it to indicate that the assumptions included in the version of the simulation used for the pulse start time might not be correct. The top one displays the full pulse range, while the bottom zooms in to highlight the difference in their rising time. This simulated pulse starts its rise approximately 10 bins (16  $\mu$ s) later than the Average Template, consistent with the shift observed in Figures 10.3 and 10.5.

## 11. CONCLUSIONS

In this chapter, we conclude the thesis by summarizing the progress and key findings of this work, as well as outlining future research directions that aim at addressing unresolved issues. While our simulations of the CDMSlite detector’s response to electron-recoil (ER) interactions incorporate an enormous amount of microphysical modeling, we observe a number of trends in our data that allow for effective macroscopic models that can be useful if properly employed. There is clear qualitative agreement between the simulated results and the real data, which gives us cause for optimism, as the simulations point to areas of clear potential analysis improvements. On the other hand, we also see important quantitative differences that give us pause. Ultimately, the utility and effectiveness of these methods moving forward depend critically on the fidelity of the simulations. Thus, summarizing the highlights of our work is important, as it is pointing out important directions for future investigation.

One of the biggest assumptions made in the previous CDMSlite analyses is that the collected phonon energy consists of fast and slow components, Fast and Slow Energy, with the former being position-dependent and the latter being evenly shared among the four phonon channels. Not only are these assumptions used in the calibration procedures, but they are also used extensively in the Optimal Filter algorithm using two templates, as described in Chapter 4. The results from those algorithms are then used in the energy estimation as well as in a quantitative estimation of the sharing of the fast component in each of the channels, which in turn is used to estimate the radial position of interactions and reject events expected to be poorly measured. In this work, we have endeavored to test these assumptions using simulations of the microphysics processes governing the CDMSlite detector’s response to interactions. We find that while the big picture description of an event as a combination of fast and slow appears to be well-founded, there appear to be a number of sub-dominant effects which must be taken into account to properly describe the data. On the other hand, given that the simulations do not match our expectations for reasons we don’t understand, the validity of the assumptions and form of the higher-fidelity effective modeling will have to be settled

by future work.

Our simulations of the CDMSlite detector response in this work have suggested useful conclusions. While the above caveats apply, and many of these conclusions are simply extensions of previous descriptions, we note that the big step forward is our understanding of the processes that affect phonon generation, the time and position of the phonon absorption, and signal/pulse interpretation. The simulations suggest that:

- There are several position-related reasons why the expected total number of phonons from an interaction might not be generated. As was previously known, charges from interactions that occur near the top/bottom surface or the sidewalls do not traverse the full voltage drop, and thus do not produce the expected amount of phonon energy. With simulation we are not only on our way to quantitatively estimate the impact of each, but if our understanding is correct then the way they do so indicates that new methods can be developed to identify and effectively reject them and methods of estimating the size of the fiducial region, and the systematic uncertainties on that estimate can be reduced.
- The previous macroscopic description of the phonon absorption by the sensors as a combination of Fast and Slow Energy appears to be well justified and has been used quantitatively in the reconstruction of the data as an average response in the simplest cases, and then corrected with position-dependent trends. While a full description of the absorption requires the simulation of the billions of microphysical absorption, reflection, scattering and decay processes, our results indicate that there are more sophisticated parameterizations that can help with analysis. If we consider an interaction at the center of a detector as a baseline, the Fast Energy can be described as consisting of about 12% of the total collected energy, and that it is collected within the first  $\sim 100 \mu\text{s}$  after an interaction. To a decent degree of approximation its spatial distribution across the detector surface can be described by a generalized Gaussian centered on the  $XY$  position of the interaction with an effective  $\sigma$  of about 7.7 mm. Slow Energy, corresponding to phonons absorbed after  $100 \mu\text{s}$ , takes the rest of the 88% and appears to be mostly uniformly collected. The shape of the Fast Energy distribution and the relative

contributions of Fast and Slow Energy appear to change smoothly as a function of  $R$ , but drastically for interactions occurring near the detector sidewall.

- The previous descriptions of the Fast Energy as having a position-dependent distribution has been useful for rejecting events which show early energy in the PA channels. Our simulations indicate that the time and value of the peak positions can provide more powerful methods for both rejecting poorly-measured events and estimating interaction positions. Simple selection criteria with the current simulation suggest that it can achieve a rejection rate of 99.0% for the poorly-measured events while retaining 77.8% of the well-measured events. Similarly they suggest that we can estimate the interaction position with accuracy up to 0.5 mm for radial position and  $1^\circ$  for angular position.
- The description of Slow Energy as having a uniform distribution has been used effectively in pulse fitting and calibration as it is a reasonable first-approximation description of the phonons that bounce multiple times before being absorbed. On the other hand, this implies that all channels should collect equal amounts of energy at late times which the simulation indicates is only approximately justified. A better description appears to be that there is small but systematically larger ( $\sim 1\%$ ) amount of phonon energy collected by the outer channel than the individual inner channels at later times of an event, which are important enough that they should be taken into account.

We next summarize several potential improvements to the analysis methodologies that could be employed if the simulations are found to have high fidelity. We find that it should allow for:

- Smaller systematic uncertainties on the estimate of the volume of the fiducial region for use in cross section and limit setting,
- Improvements to be made in the optimization process of separating between well- and poorly measured events,

- More correct calibration processes that scale the individual channel pulses. We note that while the underlying causes of the differences from the previous assumption are not yet understood, it is not obvious what methods, other than simulation-based methods, could be used with confidence.

Much of our future-work recommendations are motivated by the differences observed between simulated and real pulses. Since we only have hypotheses for the causes of the differences, the causes will need to be understood before any fixing can be completed. This suggests multiple directions, including

- Assessing the validity of the assumption that the different methods used to select the set of events in the real data and in the simulations makes their comparison useful. Although true phonon energy values are unavailable in real data, it is possible to perform this investigation using simulated pulses processed in the same way as real data, with the Optimal Filter algorithm applied to the simulated pulses as a first step. Of course, this can't begin in earnest until the pulse shapes from simulation match the data well-enough for the OF results on them to be considered reliable
- Getting a better understanding of the processes that govern the phonon energy and mode evolution at each stage of the pulse, which will better identify the sources of discrepancies between simulated and real data. For example, future work should explore incorporating specular phonon reflections as a tunable parameter in the simulations. Similarly, the charge transport and scattering models will need to be upgraded, as well as the inclusion of surface effects such as surface-mediated downconversion. Any such change will require a re-tuning of the relevant simulation parameters accordingly.
- Correcting the different pulse-start time offsets between simulation and real data.

The big picture conclusion from our work is that while the qualitative agreement between simulations and real data gives us cause for optimism, there are clearly issues to be understood

and problems to be fixed. In the meantime we have learned a great deal. Many of the assumptions used in previous analysis appear to be well-justified, while it appears that others are not. A number of analysis methods appear reasonable, but with a better understanding of the processes through simulation they could be improved to provide additional sensitivity in future searches. While the current simulations successfully reproduce many detector behaviors and outputs, there are clear quantitative differences between its predictions and the experiment data, suggesting a clear path forward for the next generation of microphysics modeling and analysis if we are going to be able to take advantage of this powerful tool. If an excess is observed in the data, simulations may be needed to point the way to determining how seriously it should be taken.

The nature of what we call the dark matter that fills the universe remains one of the greatest mysteries in modern astronomy and cosmology, and investigating its assumed particle properties and interactions continues to be a major challenge. The SuperCDMS experiment has had a long and storied role in these searches, and the methods of using single germanium (Ge) crystal detectors instrumented with superconducting sensors have been shown to have world-leading detection sensitivity when a large voltage bias is placed across the detector. The CDMSlite detector had the ability to measure interactions in the range of 0.1–10 keV. Its successor, SuperCDMS SNOLAB, will operate detectors with ultra-low energy thresholds that are expected to reach tens of eV [54], further enhancing the potential for a positive identification of dark matter particle interactions. We expect that this work can help point the way forward, and hope that it may ultimately contribute to the first observation of dark matter interactions in the SuperCDMS detectors during the upcoming datataking runs at SNOLAB in the next couple of years.

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## APPENDIX A

### SUPERCDCMS DETECTOR TOWER AND GEOMETRIC PARAMETERS OF THE CDMSLITE DETECTOR

In this appendix, we provide additional detail about the SuperCDMS apparatus and the CDMSlite detector as supplementary material to their descriptions in Section 2.1. The central chamber of the SuperCDMS apparatus, shown in Figure 2.1, contains the full set of detectors. Figure A.1 shows the detector array within it, which consists of five towers, each containing three detectors, along with a diagram of the two charge channels and four phonon channels on the top and bottom surfaces of each detector. Figure A.2 shows a mechanical drawing of the CDMSlite detector, with a summary of the relevant geometric parameters given in Table A.1. The exact mechanical sizes of the detector are used in the simulations as described in Section 5.1, and the details can affect the distributions of the response quantities as described in Section 6.2.

Some of the mechanical details can, in principle, affect the results, and some, but not all, are included in our simulations. For example, the position of the CDMSlite detector within all the other components and relative to the position of the Cf-252 source is expected to have some impact on where and how the neutrons will interact with the CDMSlite detector after their travel from the source position during the times when the Cf-252 source is inserted for calibrations, as described in Section 2.2. This in turn impacts where the Ge atoms will be activated, and eventually decay. While the simulation infrastructure can fully model these processes, they are not included in the simulation samples used in this for simplicity. As described in Section 5.2, all samples are generated as a uniform distribution of events within the detector. This work assumes that the impact of any differences are negligible, but future work can take into account a more sophisticated expected distribution.

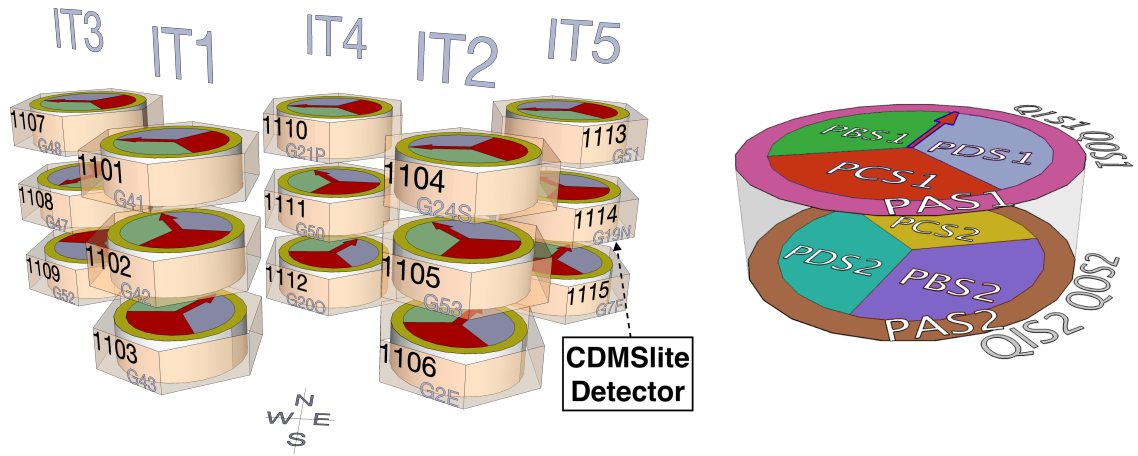


Figure A.1: This figure shows both the SuperCDMS detector towers which are located in the center portion of the SuperCDMS apparatus (see Figure 2.1) and a detailed channel map of an individual detector. We show it to illustrate the location and layout of the components of the CDMSlite Detector (1114) that is used in our analysis. As shown on the left, the array has five towers, labeled as IT1-IT5, each with three detectors aligned vertically (labeled from 1101-1115). The right shows the original two-sided readout of the detector prior to being converted for use in CDMSlite mode. The two sides are labeled as S1 and S2. Each side has four phonon channels, labeled as PA, PB, PC, and PD, and an inner and outer charge channel, labeled as QI and QO. Figures courtesy of the SuperCDMS Collaboration.

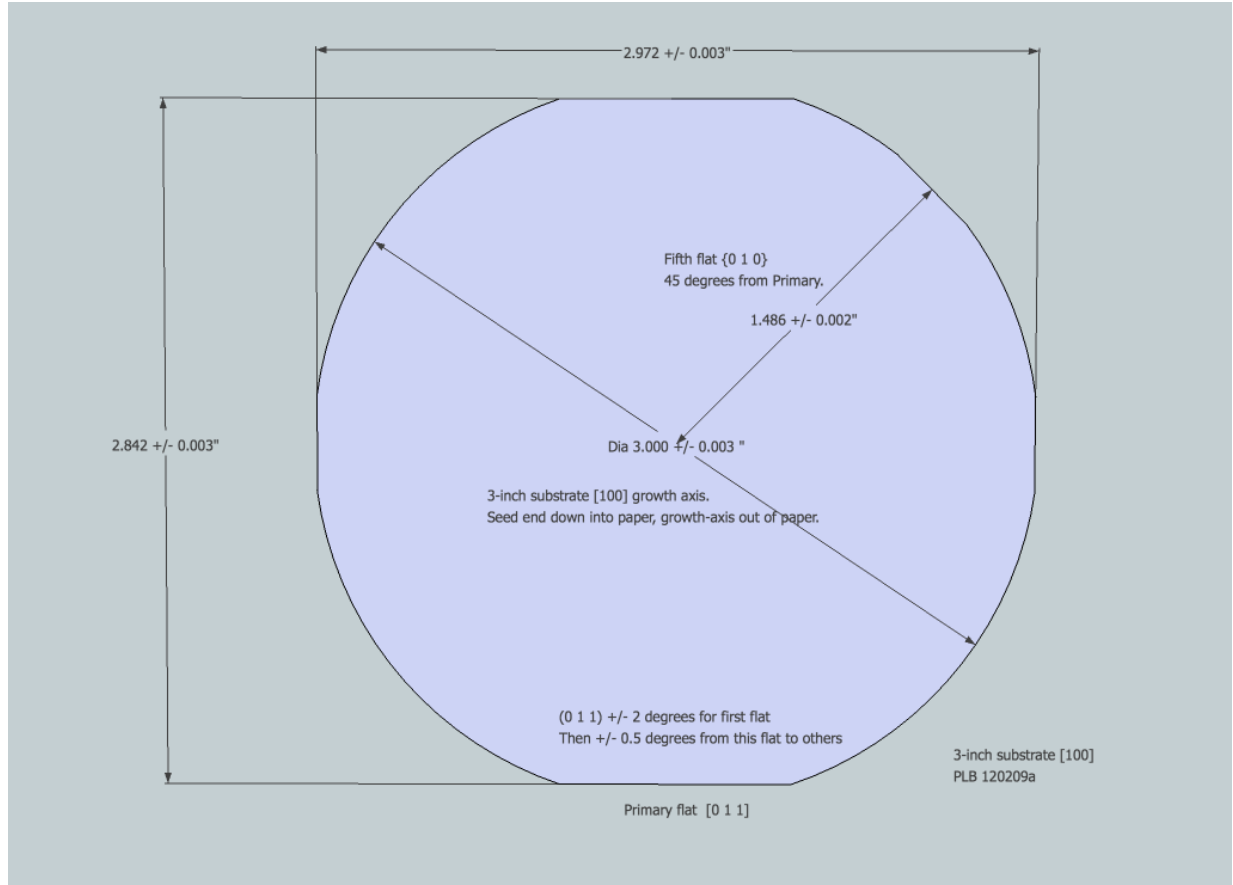


Figure A.2: This figure shows a mechanical drawing of the CDMSlite top/bottom surface. We show it to give the geometric parameters of the detector which are collected in Table A.1 and used in the simulations. Figure courtesy of the SuperCDMS Collaboration.

| Geometric Detector Parameters            | Value                                           |
|------------------------------------------|-------------------------------------------------|
| Diameter                                 | 3.000 $\pm$ 0.003 inches (76.20 $\pm$ 0.08 mm)  |
| Radius                                   | 1.500 $\pm$ 0.0015 inches (38.10 $\pm$ 0.04 mm) |
| Distance between flats (top and bottom)  | 2.842 $\pm$ 0.003 inches (72.19 $\pm$ 0.07 mm)  |
| Distance between flats (right and left)  | 2.972 $\pm$ 0.003 inches (75.49 $\pm$ 0.08 mm)  |
| Distance from center to upper right flat | 1.486 $\pm$ 0.002 inches (37.74 $\pm$ 0.05 mm)  |

Table A.1: This table lists the geometric parameters of the CDMSlite detector as shown in Figure A.2 which are used in the simulations.



## APPENDIX B

### SOFTWARE VERSIONS AND PARAMETER VALUES USED IN THE CREATION OF SIMULATION SAMPLES

In this appendix, we specify the versions of the simulation software and scripts described in Chapter 5 and used to create the simulation samples utilized in this work, along with the most important values of the physical parameters used in DetectorSim that affect the pulse shape. They are listed in Tables B.1 and B.2, respectively. Documenting those numbers and parameters ensures the reproducibility and proper interpretation of the simulation results presented in this work. We note that while most of the parameter values listed in Table B.2 are the default values used in the software versions listed in Table B.1, the values of *PhononAbsTop* and *TESsubgapAbsorption* are not. Each was selected based on the results of a tuning procedure to make the sum of the TES channel output pulses match the Average Template as shown in Figure 4.2.

| Software         | Version               |
|------------------|-----------------------|
| SuperSim         | supersim-V09-13-00    |
| Geant4           | geant4-10-06-patch-02 |
| G4CMP            | g4cmp-V08-04-01       |
| EPotFiles        | epotfiles-V00-00-06   |
| SimWorkFlowTools | v5.5.0-0-gf2d9761     |
| SimProdMacros    | V01-08-00-0-ga8b1818  |

Table B.1: This table lists the version numbers of the software used to in Chapter 5 to produce the simulated samples used throughout this work.

| Parameter           | Description                                                                                                                                                             | Value                  |
|---------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|
| PhononAbsQETs       | Probability of a phonon being absorbed upon hitting an Al QET pad                                                                                                       | 0.45                   |
| TESsubgapAbsorption | Probability for TES to directly absorb phonons below Al bandgap                                                                                                         | 0.5                    |
| PhononAbsTop        | Probability of a phonon being absorbed upon hitting the bare top detector surface (between QETs)                                                                        | 0                      |
| PhononAbsBottom     | Probability of a phonon being absorbed upon hitting the bare bottom detector surface (between QETs)                                                                     | 0                      |
| PhononAbsSide       | Probability of a phonon being absorbed upon hitting the detector sidewalls                                                                                              | 0                      |
| PhononSpecQETs      | Probability of specular reflection when a phonon hits the QETs (0 means fully diffusive reflection and 1 fully specular reflection)                                     | 0                      |
| PhononSpecTop       | Probability of specular reflection when a phonon hits the bare area of the top detector surface (0 means fully diffusive reflection and 1 fully specular reflection)    | 0                      |
| PhononSpecBottom    | Probability of specular reflection when a phonon hits the bare area of the bottom detector surface (0 means fully diffusive reflection and 1 fully specular reflection) | 0                      |
| PhononSpecSide      | Probability of specular reflection when a phonon hits the detector sidewalls (0 means fully diffusive reflection and 1 fully specular reflection)                       | 0                      |
| ElectrodeThickness  | Thickness of QET films in nm                                                                                                                                            | 600                    |
| phononBounces       | Maximum phonon reflections allowed                                                                                                                                      | 20000                  |
| energyGap           | Single electron bandgap in Ge ( $\Delta$ not $2\Delta$ ) in $\mu\text{eV}$                                                                                              | 173.715                |
| decay               | Energy-dependent scale phonon anharmonic decay coefficient [ $\text{s}^4$ ]                                                                                             | $6.43 \times 10^{-55}$ |
| scat                | Energy-dependent scale phonon isotopic scattering coefficient [ $\text{s}^3$ ]                                                                                          | $3.67 \times 10^{-41}$ |

Table B.2: This table lists the most important parameters used in DetectorSim along with the values and description of each. We provide them as each has an impact on the phonon processes which affects the collection and channel output shapes. We note that the values of *PhononAbsQETs* and *TESsubgapAbsorption* are custom for the creation of the samples used in this work (obtained from the pulse shape tuning process), while the others are default values for the software version listed in Table B.1.

## APPENDIX C

### FAST ENERGY DISTRIBUTION FOR DIFFERENT INTERACTION POSITIONS

In this appendix, we present a series of figures to illustrate the distributions of the collected phonon energy for time  $< 100 \mu\text{s}$  as shown in Figure 7.7, but where the interaction occurs at different radial positions ( $R$ ) along the y-axis. This helps us understand qualitatively the more complicated expectations for the Fast Energy distribution as the interaction position changes. In the previous study described in Sections 7.2 and 7.3, we modeled the Fast Energy distribution using the EPot\_hits sample, which consisted of a single simulated event at the center of the CDMSlite detector ( $R = 0$ , corresponding to  $X = 0$  and  $Y = 0$  and  $Z = 0$ ), and considered the set of QETs as shown in Figure 7.3. We expect that when an event occurs at larger  $R$ , there will be impact both on the transport of the charges because of variations in the electric field as well as impact on the early phonons as they are more likely to interact with the detector sidewalls, thereby affecting the spatial distribution of Fast Energy. The distributions will also be affected by the spacing and locations of the individual QETs on the surface. The prediction is that the distribution will remain approximately Gaussian-like until the largest values of  $R$ , but with changes in both the total amount of Fast Energy and the distribution shape parameters.

To test this hypothesis, we created several similar samples but changing only  $Y$  so its position was at  $R = 5, 10, 15, 20, 25$ , and  $30$  mm. The distributions of the collected phonon energy for time  $< 100 \mu\text{s}$ , along with the best-fit generalized Gaussian functions, are shown in Figure C.1. The corresponding best-fit parameters are summarized in Table C.1. The distribution shape clearly varies as  $R$  increases: the amplitude  $A$  generally decreases, while the shape parameters  $\alpha$  and  $\beta$  appear to fluctuate within their uncertainties. Although this variation is not further investigated in this work, it is consistent with the expectations that the distorted electric field at larger  $R$  also biases the trajectories of charge carriers, thereby broadening the spatial distribution of phonons at earlier times. Similarly, phonons that reflect diffusely off the sidewall are more likely to have a delay in

their first arrival at the detector surfaces, moving them from being in the fast component to being in the slow component.

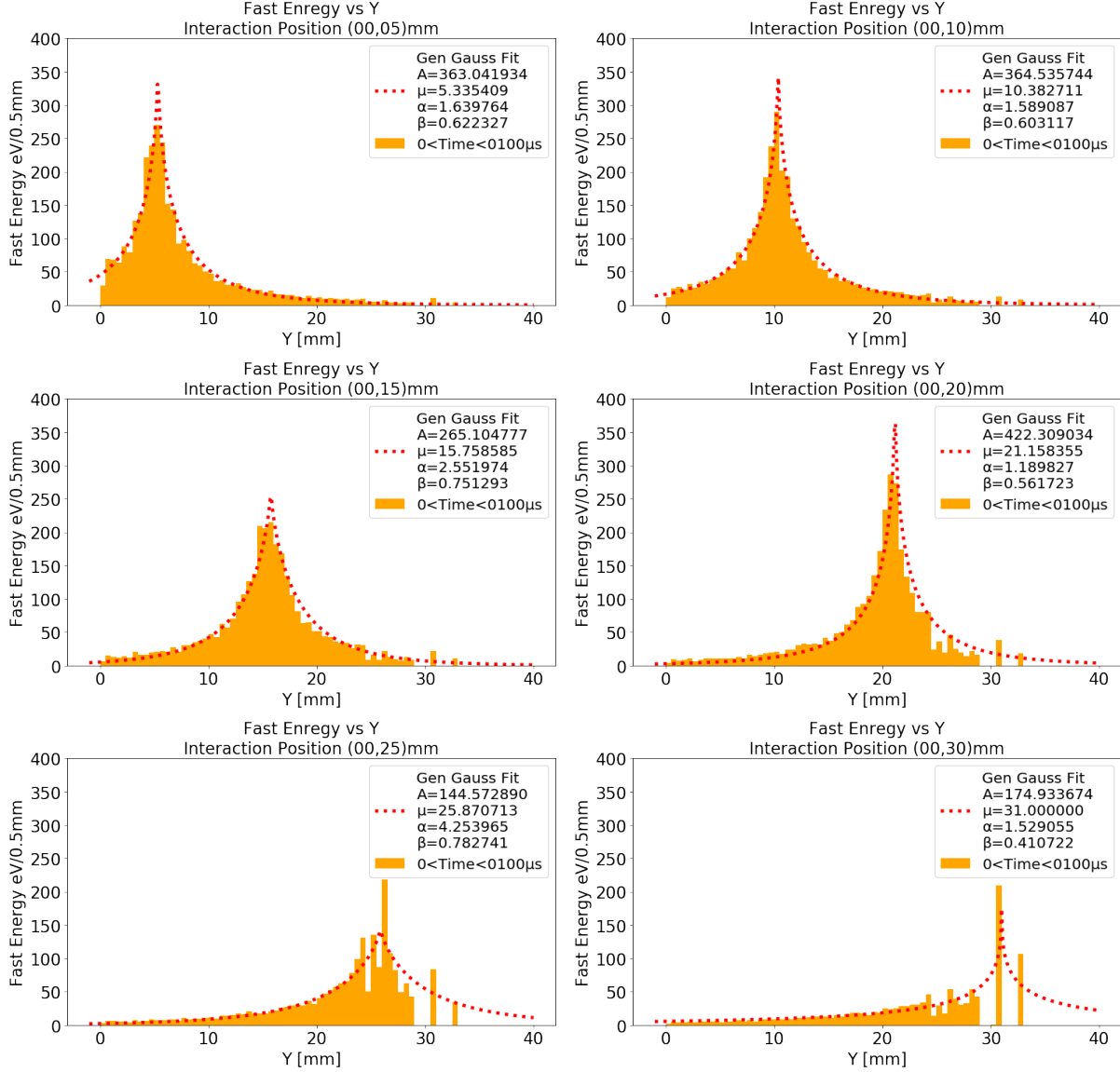


Figure C.1: This figure shows the distribution of phonon energy collected by the same set of QETs as in Figure 7.3 for time < 100  $\mu$ s, but for six different positions along the Y-axis. We show it to illustrate the size and shape of the fast component as a function of  $R$ . We set the values of  $Y$  to 5, 10, 15, 20, 25 and 30, with  $X$  and  $Z$  fixed to 0. The best-fit generalized Gaussian parameters are shown in the legend of each plot and also listed in Table C.1 for easier comparison.

| interaction<br>position, $R$ [mm] | distribution<br>parameters | $A$ [eV] | $\mu$ [mm]            | $\alpha$ | $\beta$ |
|-----------------------------------|----------------------------|----------|-----------------------|----------|---------|
| 0                                 |                            | 406      | $-6.6 \times 10^{-6}$ | 3.55     | 0.80    |
| 5                                 |                            | 363      | 5.3                   | 1.6      | 0.62    |
| 10                                |                            | 364      | 10.4                  | 1.6      | 0.60    |
| 15                                |                            | 265      | 15.8                  | 2.6      | 0.75    |
| 20                                |                            | 422      | 21.2                  | 1.2      | 0.56    |
| 25                                |                            | 145      | 25.9                  | 4.3      | 0.78    |
| 30                                |                            | 175      | 31.0                  | 1.5      | 0.41    |

Table C.1: This table lists the best-fit parameters of the generalized Gaussian distribution (Equation 7.2) for the absorbed phonon energy distributions with time  $< 100 \mu\text{s}$  from Figures 7.7 and C.1 at a number of different radial positions.

## APPENDIX D

### ESTIMATING THE INTERACTION POSITIONS USING COLLECTED PHONON ENERGY IN THE CHANNELS

In this appendix, we present a series of figures like those in Section 8.3 for use in comparing the potential position measurement resolution when we use the collected phonon energy in each channel instead of the information contained in the peaks of the power distributions. In that section, we used *Val542* to estimate both  $R$  and the angular positions of an interaction and found it to be highly effective for the reasons described there. On the other hand, while *Val542* is clearly very powerful, this is one of the quantities where we see significant differences between real data and simulation. While we do not typically use the direct estimates of the channel-by-channel energies in the real data, we expect this quantity to be more robust against the simulation problems that affect the individual power distributions. Even without optimal filtering methods, simple estimation methods like integrating the area under the current curves of signals have been shown to provide decent estimates when the pulse is large.

The methodology for estimating the position is the same as in Section 8.3. For simplicity, we simply show the results for the  $R$  estimation as sensitivities for the angular position are similar. As expected, Figure D.1 shows that the ratio of the amount of phonon energy collected by the outer channel ( $PhE_A$ ) to that by the summed inner channels ( $PhE_{BCD}$ ) varies as a function of  $R$ . While the variation isn't as significant as that shown in Figure 8.9, the value of  $R$  can still be readily estimated. We find similar results for Figures 8.10 - 8.12. A comparison of the accuracies using these methods and those using *Val542* is given in Figure D.2. While this method also provides valuable information for position estimation, the results using *Val542* are always better.

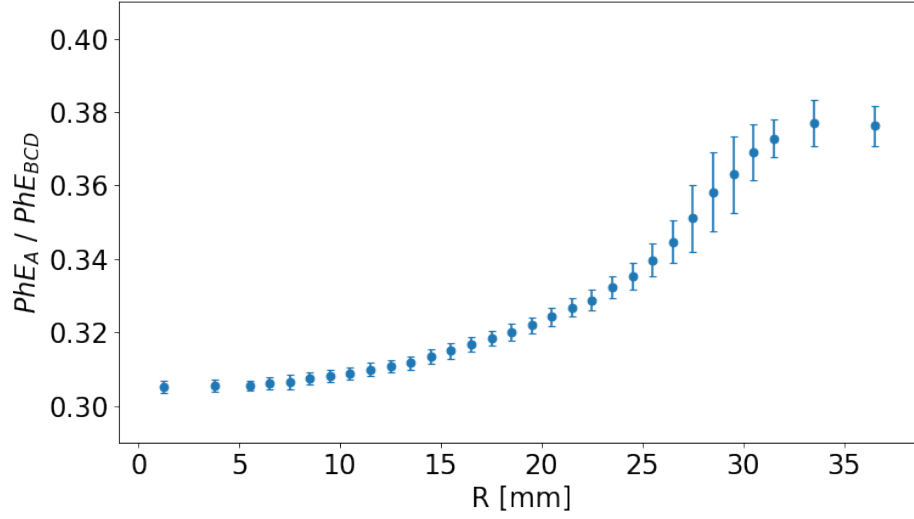


Figure D.1: This figure is the same as Figure 8.9, but where we show the ratio  $PhE_A/PhE_{BCD}$  as a function of the radial position ( $R$ ) of an interaction for the well-measured events in the simulated EPot sample. We show it because this ratio allows for an estimate of the  $R$  for an event.

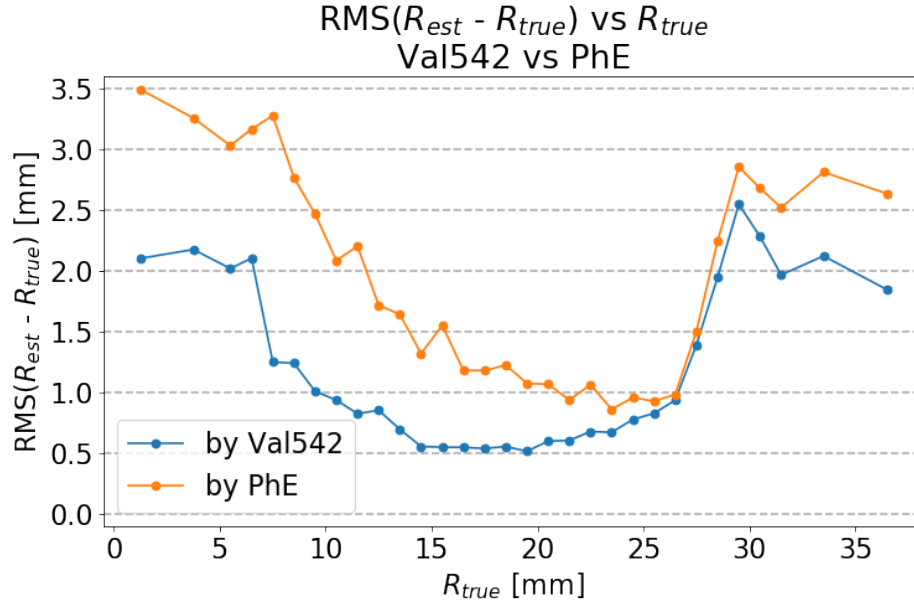


Figure D.2: This figure shows the comparison of  $RMS(R_{est}-R_{true})$  from Figure 8.14 (blue) to those determined using  $PhE_A/PhE_{BCD}$  as shown in Figure D.1 (orange). We show it to illustrate that while the estimation of  $R$  using the collected phonon energy in channels (‘PhE’) gives similar results as *Val542*, the later always provides better accuracy, but assumes more parts of the simulation have high fidelity.