Study of background from accidental coincidence signals in the PandaX-II experiment

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Abstract

The PandaX-II experiment employed a 580kg liquid xenon detector to search for the interactions between dark matter particles and the target xenon atoms. The accidental coincidences of isolated signals result in a dangerous background which mimic the signature of the dark matter. We performed a detailed study on the accidental coincidence background in PandaX-II, including the possible origin of the isolated signals, the background level and corresponding background suppression method. With a boosted-decision-tree algorithm, the accidental coincidence background is reduced by 70% in the dark matter signal region, thus the sensitivity of dark matter search at PandaX-II is improved.

Keywords: dark matter, xenon detector, background, accidental coincidence, machine learning

1 Introduction

The direct detection of the dark matter particles, especially the weakly interacting massive particles (WIMPs), is actively carried out by a couple of experiments all over the world currently [1]. In recent years, the PandaX-II experiment located in the China Jinping Underground Laboratory (CJPL) [1, 2, 3], which uses the technology of dual phase liquid xenon time projection chambers (TPCs), has pushed the limits of cross section between WIMPs and nucleons to a new level for most of the possible WIMP masses, with other experiments of the same type [4, 5, 6, 7, 8, 9, 10]. The scattering of incident particles with xenon atoms in the TPC may produce a prompt scintillation $S_1$, which resulted from the de-excitation of xenon atoms and the recombination process of some ionized electrons. Some electrons escaping from the recombination may drift along the electric field inside the TPC and be extracted into the gaseous region, producing the proportional electroluminescent scintillation $S_2$ [11, 12]. The detected signals of $S_1$ and $S_2$ are used to reconstruct the scattering event in the data analysis. Due to the low probability of scattering events between WIMPs and ordinary matter, a good physical event requires only one pair of physically correlated $S_1$ and $S_2$ within the maximum electron drift time window inside the TPC. In the last results of the PandaX-I experiment [13], it was realized that the accidental coincidence of isolated $S_1$ and $S_2$ within the window comprises a new type of background, which contributes a number of events in the signal parameter space to search for WIMPs. Understanding this type of background and development of methods to suppress it become important for the improvement of dark matter detection sensitivity. In the data analysis of PandaX-II with the full exposure, we made a thorough study of the accidental background and presented an accurate estimation of its level for all the three data taken runs, 9, 10 and 11 [4].

In this article, we present a detailed introduction on the study of accidental background in PandaX-II. In Section 2, we provide a brief introduction to the PandaX-II TPC, the signals and the backgrounds. Then we discuss the possible origin of the accidental background in Section 3. The estimation of its level is presented in Section 4. The application of the boost-decision-tree (BDT) method to suppress the background is given in Section 5, with the performance presented. At last, we give a brief summary and outlook in Section 6.
2 TPC, signals and backgrounds of PandaX-II

A detail description of PandaX-II TPC is presented in Ref. [7]. A more detailed schematic view of the TPC is presented in Figure 1. The near-cylindrical shaped TPC confined by polytetrafluoroethylene (PTFE) walls, contains both of gaseous xenon (top) and liquid xenon (bottom) in its volume. Scintillation light generated inside the TPC is detected by the two arrays of photo-multiplier tubes (PMTs) located on the top and bottom region, respectively. The cathode in the bottom part of the TPC and the gate electrode right below the liquid surface, provide the drift electric field for ionized electrons and define the sensitive region of the detector (region 1 in Figure 1).

![Figure 1: Schematic view of the TPC of PandaX-II, with six regions labeled with numbers: 1. the liquid part below the gate and above the cathode; 2. the liquid part below the cathode; 3. the liquid part above the gate; 4. the gas part below the anode; 5. the gas part above the anode; 6. parts outside the inner PTFE walls. A recoil event in region 1 may produce $S_1$ and $S_2$ signals at different regions in the detector with a time delay.

Deposited energies by scattering events inside the sensitive region result in a $S_1$ signal, typically with a time spreading$^1$ smaller than 150 ns, in very short time, while the possible $S_2$ signal will be produced after a time delay, due to the limited drift velocity of ionized electrons inside liquid xenon. The drift velocity of electrons depends only on the electric field strength, thus the time difference between physically correlated $S_1$ and $S_2$ can be used to calculate the vertical position of a scattering event. The maximum drift time for electrons in the sensitive region is $350 \pm 8 \, \mu s$ in Run 9 and $360 \pm 8 \, \mu s$ in Runs 10 and 11, due to the different drift fields [4]. When a “trigger” signal exceed the pre-defined threshold is observed during the ordinary data taking, the digitized waveform of all the PMTs within a window $500 \, \mu s$ before and after the trigger time is recorded as an event. The data processing steps calculate the baseline of each recorded waveform, search for “hit” exceeding a given threshold of 0.25 photoelectrons (PE) and cluster the overlapped hits into signals. Events of single scattering (with only one $S_1$ and $S_2$ reconstructed) are selected, and then filtered.

$^1$We use the term of “width” in following text to represent this concept.
by the quality cuts to search for the possible rare scattering from WIMPs.

Recognition, understanding and suppression of the different types of backgrounds are critical in the data analysis of WIMP searching experiments because the desired signal rate is very low. In the PandaX-II experiment, the backgrounds can be categorized into four types. The electron recoil (ER) backgrounds, mainly from the radioactive isotopes in the detector material or in the xenon target, have been studied and understood with the ER calibration data and Geant4-based Monte Carlo (MC) simulations [14, 15]. The nuclear recoil (NR) background, mainly from neutrons produced by the \((\alpha, n)\) process or spontaneous fission of isotopes in detectors, has been estimated by the correlated high energy gamma events with the help of simulation [16]. The surface background are created by daughters of \(^{222}\text{Rn}\) attached on the inner surface of the TPC, with suppressed \(S^2\) due to the charge loss on the PTFE wall. The level of surface background is estimated with a data driven method [4, 17]. The last one is the nonphysical accidental background resulted from the falsely pairing of unrelated \(S^1\) and \(S^2\) signals. A large proportion of the accidental background events have relatively small \(S^2\) signals, thus are not easy to be distinguished from the physical NR events (neutron or WIMPs) by investigating the ratio of \(S^2/S^1\) only. Effective suppression of the accidental background will improve the discovery sensitivity of WIMPs greatly.

3 Origins of the accidental background

In the TPC, some \(S^1\) or \(S^2\)-like signals may be produced solely, without any other signals from the same source observed by detector. We call these signals “isolated”. Since the events with a pair of \(S^1\) and \(S^2\) are used to search for dark matter, the isolated signals appearing in the same drift window may be paired, resulting in the accidental background.

3.1 The isolated \(S^1\)

The origins of isolated \(S^1\)s may be physical or non-physical. The physical origins might be in the following:

- tiny sparks on the TPC electrode, no electrons produced;
- scattering events in the region between the cathode and the screening electrode of the bottom array (region 2 in Figure 1), within which no electron could drift into the gas xenon, thus no \(S^2\) could be produced;
- physical events occur near the bottom wall of the detector with all electrons lost due to the imperfect of the drift field, thus no \(S^2\) is produced;
- scattering events above the anode in the gaseous region (region 5 in Figure 1), with no electrons entering the region below the anode to produce \(S^2\);
- signals produced by single electron extract into the gas region, which are mis-identified as \(S^1\)s;
- possible light leakage from scattering events outside the TPC (region 6 in Figure 1).

The dominant non-physical origin of isolated \(S^1\) is from the dark noise of the PMT, which produce small hits in the readout waveform of each PMT. During the event reconstruction, a valid signal should contain overlapped hits from at least three PMTs. The relatively high rate of dark noise (average rates are 1.9, 0.17 and 0.23 kHz per PMT for Runs 9, 10 and 11, respectively) makes it possible for the formation of small \(S^1\)-like signals by the randomly coincidence of the dark noises. Since these signals have contribution from the top PMTs, their top-bottom asymmetry (discussed in section 5.1) should not be \(-1\).

3.2 The isolated \(S^2\)

The \(S^2\) signals are from the electroluminescent of electrons in the gas region. The isolated \(S^2\) signals, without exception, resulted from the same process. The origin of isolated \(S^2\) can be categorized into four types:

- real scattering event in the sensitive region with small energy deposition, and the weak \(S^1\) is not recognized due to the detection efficiency;
• real scattering event in the sensitive region, but it is too close to the liquid surface, resulted in overlapped S1 and S2 signals, which are recognized as one S2;
• real scattering event in the region above the gate but below the anode (region 3 and 4 in Figure 1), with overlapped S1 and S2 signals recognized as one S2; the signal may have smaller width and asymmetrical shape;
• the electrons generated with large energy deposition may not be extracted into the gas region completely. The rest electrons gather on the liquid surface and are released into the gas randomly, producing electroluminescent directly.

4 Estimation of accidental background

Since the isolated signals are independent from each other, the level of accidental background can be calculated by the rates of isolated S1 and S2 signals, assuming they follow an uniform distribution along time in a selected period with same run conditions. Estimation of the rates of these signals becomes important in this study.

For each of the data taking run, the average rates $\bar{r}_1$ for isolated S1 and $\bar{r}_2$ for isolated S2 are computed by the time weighted average of the corresponding rates:

$$\bar{r}_1 = \frac{1}{\sum_i T_i} \sum_i r_{1i} \cdot T_i,$$

$$\bar{r}_2 = \frac{1}{\sum_i T_i} \sum_i r_{2i} \cdot T_i,$$

where $T_i$, $r_{1i}$, $r_{2i}$ are the duration, rates of isolated S1 and S2 for each selected period $i$, respectively. The uncertainties of the rates are calculated as the unbiased standard errors of the mean value.

4.1 Tagging of isolated S1

To calculate the rate of isolated S1, we need to recognize this type of signal correctly in the data. Three methods have been developed to search for the isolated S1 within the range of (3, 100) PE, which covers the energy region of searching for dark matter. One is based on a special type of “random trigger” data set, with the event triggered by hardware randomly. The other two methods are based on the dark matter search data. We describe all of these three methods here.

4.1.1 Method 1

This method is to search isolated S1 events in the random trigger data. The events should satisfy all the required data quality cuts mentioned in Ref. [4]. The rate $r_1$ in one run can be calculated easily by the $^2$

$$r_1 = \frac{n_{iS1}}{T_i},$$

where $n_{iS1}$ is the number of qualified isolated S1, and $T$ is the live time of the random trigger events. The method is unbiased, and is used to estimate the accidental background level in Run 10 [5]. Due to the short time of data taking with random trigger, the long term evolution of the rate can not be extracted. No random trigger data taking was performed in Run 9, so this method can only work in Runs 10 and 11.

4.1.2 Method 2

In this method, the isolated S1 is defined as small S1 signals before the triggered S1, which has no paired S2 within the window of maximum drift time (see Figure 2). The triggered S1 should be larger than 100 PE. The time difference $\Delta t$ (see Figure 3) between the isolated S1 and the triggered S1 is used directly in the simulation of accidental background by pairing the selected isolated S1 and S2 signals (see following section), therefore we require

$^2$The subscript “$i$” is omitted in following formulas.
that $\Delta t$ should be within the window of $(10, 350) \mu s$ for Run 9 or $(10, 360) \mu s$ for Runs 10 and 11 before the triggered $S1$, respectively, by considering the cut on the drifting time.

![Schematic view on the search of isolated S1](image)

Figure 2: Schematic view on the search of isolated S1 in events triggered by unpaired S1 ($S1_{\text{max}}$) in Runs 10 and 11. The event has a fixed time window of 1 ms, and the trigger windows is within $(490, 510) \mu s$. The symbol of “A” and “B” indicates the searching window for isolated S1.

The rate $r_1$ of isolated S1 in one data taking period, each consisting of several adjacent runs with nearly identical running conditions, can be estimated by

$$r_1 = \frac{n_{iS1}}{n_{tS1}} \cdot \frac{1}{\Delta t_{AB}},$$

(4)

where $n_{iS1}$ is the number of isolated S1, $n_{tS1}$ is the number of events triggered by unpaired S1, and $\Delta t_{AB}$ is size of the time window, which equal to 340 $\mu s$ for Run 9, and 350 $\mu s$ for Runs 10 and 11, respectively. The data taking periods have similar duration.

This method was used in the first analysis of PandaX-II [6]. By studying the distribution of $\Delta t$ in Figure 3, we found that the number of events decreased with the increasing $\Delta t$, indicating the possible physical correlation between some selected S1s. This phenomena becomes obvious in Run 11 due to the long data taking time. The correlation may come from the $^{214}\text{Bi}$$^{214}\text{Po}$ cascade decay in the region below the cathode (region 2 in Figure 1). A half-life of $173.59 \pm 12.53$ $\mu s$ is obtained by fitting the decay component of the time distribution, and the value is consistent with the half-life of $^{214}\text{Po}$ (164 $\mu s$). Thus the hypothesis is supported, and method 2 results in an over-estimated rate of isolated S1. The average rate could be corrected by subtracting the contribution from the $^{214}\text{Bi}$$^{214}\text{Po}$ events, with additional uncertainty introduced by the correction.

### 4.1.3 Method 3

This method searches for isolated S1 before a good event, which is triggered by S1 signal larger than 100 PE and paired with S2 larger than 10,000 PE (see Figure 4 for details). The isolated S1 is required to be before the maximum drift time of the S2 signal, i.e., 350 $\mu s$ for Run 9 and 360 $\mu s$ for Runs 10 and 11, to ensure no correlation between the isolated S1 and the S2 in the good event. The cascaded decays of $^{214}\text{Bi}$$^{214}\text{Po}$ could not enter into the data selection because two large S2 signals are expected if they happen in the sensitive region.

In this method, the rate $r_1$ in a data taking period can be estimated as

$$r_1 = \frac{n_{iS1}}{\sum (t_{s2} - \Delta t_{A2})},$$

(5)

where $n_{iS1}$ is the total number of isolated S1. The variables of time are defined in each of the good event, with $t_{s2}$ as the start time of the S2 signal relative to the start of the event, and $\Delta t_{A2}$ as the size of the exclusion window, which takes the same value as the maximum drift time.

We studied the distribution of time difference $\Delta t$ between the isolated S1 and the good S1, as shown in Figure 5. Considering the uniformity separation of the physical S1 and S2
Figure 3: Distribution of the time difference $\Delta t$ between the isolated $S_1$ and the triggered $S_1$ in method 2.

Figure 4: Schematic view on the search of isolated $S_1$ in events triggered by $S_1$ ($S_{1\text{max}}$) in Runs 10 and 11.

signals, the requirement of the isolated $S_1$ outside the maximum drift window reduces the probability of isolated $S_1$s with small $\Delta t$ to be selected. Because the selection window is reduced in the same time, the rate calculation is not affected. This behavior is reproduced with a simple toy MC simulation by randomly sampling $S_2$ after the triggered $S_1$ in the drift window and randomly sampling isolated $S_1$ in the whole event window, especially for Run 9. The same MC simulation can also be used to verify the rate calculation. Assuming the rate of isolated $S_1$ is 500 Hz, the rate calculated with method 3 is 498.9 Hz, showing a good accuracy. For Run 10, the behavior is not visible due to the relative low statistics of the isolated $S_1$. For Run 11, excess isolated $S_1$s (11.6%) are observed for $\Delta t < 120 \mu s$. They are found in the events accumulated in the cathode region, as illustrated in Figure A.1 in Appendix A. The origin of these signals is still unknown.

4.2 Tagging of isolated $S_2$

The estimation of the rate $r_2$ for isolated $S_2$ is more straightforward in comparison with isolated $S_1$. The events triggered by unpaired $S_2$, with all the related quality cuts applied, are selected to calculate the rate. The rate is defined as

$$r_2 = \frac{n_{1S2}}{T},$$  \hspace{1cm} (6)
Figure 5: Distribution of the time difference $\Delta t$ between the isolated $S1$ and the triggered $S1$ in method 3. a: Raw distribution. b: The integration of the distribution is normalized to 1.

where $n_{iS2}$ is the number of events satisfying the selection criteria, and $T$ is the duration of the run.

4.3 Properties of isolated signals

The estimated average rates of isolated $S1$ and $S2$ in each run are presented in Table 1. Run 9 has the highest rate of isolated $S1$, which is very likely to be attributed to the higher dark rate of PMTs operating with higher gain [5]. For Runs 10 and 11, the $\bar{r}_1$ calculated with method 1 and method 3 are consistent with each other within uncertainty. The results of method 3 are used in the final analysis of PandaX-II [4] and rest of this study to estimate the rate of accidental background. The variance of the average rates of isolated $S2$ is small.

| Run | Duration [days] | $\bar{r}_1$ [Hz] | $\bar{r}_2$ [Hz] |
|-----|----------------|------------------|------------------|
|     |                | Method 1 | Method 2 | Method 3 | Method 3 | Method 3 |
| 9   | 79.6           | -       | 1.40 ± 0.25 | 1.53 ± 0.16 | 0.0121 ± 0.0002 |
| 10  | 77.1           | 0.46 ± 0.05 | 0.27 ± 0.20 | 0.47 ± 0.02 | 0.0130 ± 0.0007 |
| 11  | 244.2          | 0.77 ± 0.06 | 0.37 ± 0.16 | 0.69 ± 0.06 | 0.0121 ± 0.0001 |

Table 1: Average rates of isolated $S1$ and $S2$ extracted from PandaX-II data. The results from method 2 have been corrected by subtracting the contamination from the possible $^{214}\text{Bi}^{214}\text{Po}$ cascade decay signals.

More detailed evolution of rates of the isolated signals during the whole PandaX-II data taking period, with those of isolated $S1$ calculated by method 3, is presented in Figure 6. The rate of isolated $S2$ keeps stable, while that of isolated $S1$ varies greatly. The large variance of $r_1$ in Run 9 might come from the occasional sparking of electrodes or PMTs. A peak rate of isolated $S1$ is observed in Run 11, which can be explained by the fact that some PMTs were unstable during the corresponding period, as shown in Figure A.2 in Appendix A. The ordinary data quality cut cannot remove related events efficiently.

The charge spectra of isolated signals selected by method 3 are shown in Figure 7. Most of the isolated $S1$ are found to be smaller than 10 PE. All the $S1$ spectra have similar shape when the charge is larger than 6 PE, but a higher peak is observed below 6 PE for Run 9. This may be explained by the higher chance of accidental coincidence of hits from dark current in this run due to the higher operation voltage of the PMTs. A small peak in Run 11 around 10 PE is resulted from the unstable PMTs mentioned before (see Figure A.3 in Appendix A). The spectra of isolated $S2$ are consistent with each other.

4.4 Study of the accidental background with simulation

A data-driven MC simulation with the selected isolated signals is used to study the accidental background events. For each Run, the isolated $S1$ and $S2$ are paired randomly,
Figure 6: Evolution of rates of the isolated signals during the whole PandaX-II data taking period, selected by method 3.

Figure 7: Charge spectra of isolated signals selected by method 3.

with the time separation between them sampled uniformly in the time window $\Delta t_w$ defined by the fiducial volume cut. The horizontal position of the event is determined by the $S_2$ signal. The paired mock event is treated as an event with raw signals. The same position-dependent charge corrections and quality cuts for dark matter search data are applied to these events, resulted in a cut efficiency $\epsilon$.

Then the total number $n_{\text{acc}}$ of accidental background events can be calculated by

$$ n_{\text{acc}} = \bar{r}_1 \cdot \bar{r}_2 \cdot \Delta t_w \cdot T \cdot \epsilon. \quad (7) $$

The efficiency $\epsilon$, the total number of accidental events, and the number of events below the median line of the NR band from calibration data [4] results, are presented in Table 2. Run 11 has the larger number of accidental background events due to the largest duration $T$.

The distributions of $\log_{10}(S_2/S_1)$ vs. $S_1$ for the simulated accidental background events after all the quality cuts within the dark matter search window [4] are given in Figure 8, together with those of the NR calibration data. Most of the accidental events have a relative small $S_1$ charge and are above the NR median. Considering the low statistics of the most critical ER backgrounds below the NR median, the non-negligible accidental background in this region will reduce the discovery power for WIMPs. Suppressing these background could improve the sensitivity of the detector for WIMP search.
Table 2: Number of accidental events estimated with the selected isolated signals using method 3.

| Run | Type                  | $\epsilon$ | $n_{acc}$  |
|-----|-----------------------|------------|------------|
| 9   | total                 | 21.9%      | 8.15 ± 0.94|
|     | below NR median       | 3.5%       | 1.31 ± 0.15|
| 10  | total                 | 25.6%      | 3.16 ± 0.15|
|     | below NR median       | 8.5%       | 1.06 ± 0.05|
| 11  | below NR median       | 5.6%       | 2.93 ± 0.27|

Figure 8: Distribution of $\log_{10}(S2/S1)$ vs. $S1$ for the simulated accidental background and NR calibration data. The red curves are the corresponding NR median for each Run.

5 Suppression of accidental background with BDT

The accidental events are composed with isolated $S1$ and $S2$. Since there are no physical correlation between them, we would expect a method to distinguish them from the physical events by considering the joint distributions of the properties of these signals. Because all the selected accidental events have passed the quality cuts, it is hard to tell the difference between any single property of a signal from the accidental events and the physical events. A multi-variant analysis could be used. The algorithm of BDT, as one of the most successful multi-variant analysis method used in particle physics [18], was firstly used to suppress the accidental background in the first analysis results of PandaX-II [6]. The real signal of the WIMP-nucleon scattering is NR, thus the single scattering events from NR calibration runs (AmBe) should be used as input signals in the machine learning, with randomly paired events as backgrounds. Given the fact that the ER events dominate the region above the NR median in the dark matter search data and the relative low estimated number of accidental events in the region, we only consider to distinguish the accidental background from the physical NR events below the NR median.

5.1 Variables

The TMVA (Toolkit for Multivariate Data Analysis) package in ROOT is used to perform the BDT machine learning [19]. A set of signal properties are exploited to search for the difference between the accidental events and the physical NR events, including
• corrected charge of S1 (qS1);
• corrected charge of S2 (qS2);
• raw charge of S1 (qS1R);
• raw charge of S2 (qS2R);
• width of S2 (wS2);
• full width at tenth maximum of S2 (wTenS2);
• asymmetry between the top charge and the bottom charge for S1 (S1TBA);
• ratio of the top charge to the bottom charge for S2 (S2TBR);
• the ratio of the pre-max-height charge to the total charge of an S2 signal (S2SY1 in the directly summed over waveform, S2SY2 in the smoothed waveform);
• number of local maximums (peaks) of S1 (S1NPeaks);
• ratio of the largest charge collected by the bottom PMT of S1 to total charge of S1 (S1LargestBCQ)

Distributions of these variables for the events below the NR median can be found in Figure 9, and their correlations are presented in Figure A.5.

5.2 BDT results

We constructed the adaptive BDT using the default parameters provided by the official ROOT TMVA classification example, except the parameter of NTrees (number of trees). We trained the data for the three runs independently, each with a predefined set of NTrees. After the training, the resulted BDT response distributions of the training and test data samples are superimposed and the Kolmogorov-Smirnov (K-S) test is performed to check for overtraining (see Fig. A.4 for details). We choose NTrees = 90 for further study. With the trained BDT, the “likelihood” estimators can be calculated for an input event to be classified. The best cut criteria for the estimator is obtained with the test data set by maximizing the significance S,

\[ S = \frac{\epsilon_s n_s}{\sqrt{\epsilon_s n_s + \epsilon_b n_b}} \]  

where \( n_s \) and \( n_b \) are the number of signal and background events, respectively, \( \epsilon_s \) and \( \epsilon_b \) are the efficiencies for signal and background events at a given estimator value, respectively. In this study, the expected signal events below the NR median have high probability to be the neutron background or the WIMP events, they are estimated at the same level as the accidental background [4]. Therefore, the identical numbers of \( n_s \) and \( n_b \) are used to calculate the significance. The evolution of the background rejection efficiency with the signal efficiency at different BDT cut values is shown in Figure 10. The results at the maximum significance \( S \) are presented in Table 3. The BDT algorithm is capable to remove 70% of the accidental background events, while keeping about 90% of the single scattering NR events below the NR median curve in all of the three runs. The distributions of the BDT cut efficiency on the log_{10}(S2/S1) vs. S1 plane for the simulated accidental background are given in Figure 11.

| Run | S  | \( \epsilon_s \) | 1 - \( \epsilon_b \) |
|-----|----|----------------|-------------------|
| 9   | 25.9| 90.4%          | 70.2%             |
| 10  | 26.5| 91.1%          | 74.6%             |
| 11  | 26.2| 90.7%          | 73.7%             |

Table 3: The significance \( S \), signal efficiencies \( \epsilon_s \) and background rejection efficiencies 1 - \( \epsilon_b \) at the best cut value of the estimator for events below the NR median lines, assuming \( n_s = n_b \).

The contribution of each input variable to the discrimination power is extracted by the BDT training. The variables of wS2, S2SY2, S1TBA are found to be the most critical to the recognition of accidental backgrounds. By checking the distributions of these variables,
isolated $S_2$ signals are found to have smaller width ($w_{S2}$) and more asymmetrical shape ($S2SY2$) in comparison with those in normal events, indicating that most of these signals are generated near the grid wires \[20\]. The peak in the $S1$TBA distribution of physical events at the value of -1 suggests a large fraction of the physical $S_1$ signals have no hits on the top PMT array. Given the fact that physical $S_1$s are produced inside the liquid xenon, small signals have smaller chance to be detected by the top PMTs due to the total reflection on the surface between the liquid and gas xenon. But some of the non-physical $S_1$s are from the coincidence of dark noises on the top PMTs, resulted in a $S1$TBA larger than -1. The distribution of $S1$TBA could be used to estimate the fraction of isolated $S_1$s from the coincidence of dark noise from top PMTs. This phenomenon helps to distinguish the non-physical small $S_1$ signals from the real ones.

5.3 Overall results

In the analysis, the BDT cut is not only applied to the events below the NR median, but applied to all the events in the search window. The efficiencies of BDT to different types of events are extracted by using the calibration data sets, shown in Figure 12. The BDT cut efficiencies for the ER and NR calibration data expressed as functions of $S_1$, are used to build the final signal model \[21\]. The efficiencies for ER events are lower than those of NR events when $S_1 < 8$ PE, in all of the data set. From the 2D efficiency maps, it is observed that in the region of low $S_1$, the ER events with a higher ratio of $S2/S1$ are suppressed heavily in Runs 10 and 11. On the contrary, more ER events with smaller $S2/S1$ in the same region are suppressed in Run 9. The different distributions of $S2$ related variables of the different ER calibration data may result in the different efficiencies. The distribution of $\log_{10}(S2/S1)$ vs. $S1$ of accidental background after the BDT cut are used directly in the model.

The expected numbers of accidental background (below NR median) in PandaX-II full exposure data set after the BDT cuts are $2.09 \pm 0.25 (0.39 \pm 0.05)$, $1.03 \pm 0.05 (0.27 \pm 0.01)$ and $2.53 \pm 0.24 (0.77 \pm 0.07)$ for Runs 9, 10, and 11, respectively. The total number of expected accidental background events below NR median is smaller than 1.5. Considering that the total data taking period of PandaX-II is 244.2 days, we have successfully suppressed the accidental background to a trivial level and improved the final sensitivity for dark matter search \[4\].

6 Summary and Outlook

The accidental background is an important composition of the backgrounds in the dark matter search experiments with dual phase xenon detector. We discussed the possible origins of the two components, isolated $S_1$ and $S_2$, and developed methods to estimate the level of accidental background in the PandaX-II experiment. The BDT algorithm is used to distinguish this non-physical background from real NR signals below the NR median lines, so that the level of this background is suppressed greatly.

We found that the rate of isolated $S_1$ is much higher in Run 9, during which the PMTs are running with higher gains than in other runs. This suggests the coincident combination of hits created by dark noise contributes a large amount to the isolated $S_1$. Thus reducing the dark noise of PMTs is critical for next generation of experiments \[22, 23, 24\].

The BDT method works well in the suppression of the accidental background in our study. The analysis framework and suppression method can be used in the data analysis of the subsequent PandaX-4T experiment \[25\]. Because the number of accidental events is nearly proportional to the operation time, only a few of them have been produced in the commissioning run. They have been suppressed to a very low level with the quality cuts and therefore this method is not used in the first PandaX-4T WIMP search. But PandaX-4T and other similar experiments will be running much longer than PandaX-II, our study provides a valuable reference to them. With the rapid development of the machine learning methods in recent year, we may expect the methods of neural networks or some others may achieve equivalent success in this topic.
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A Complementary plots
Figure 9: Distribution of the selected variables from the NR calibration data (signal) and the simulated accidental events (background) in Run 11. Only the events below the NR median are selected.
Figure 10: The evolution of the background rejection efficiency with the signal efficiency at different BDT cuts for different runs. The initial numbers of background and signal events are assumed to be identical.

Figure 11: BDT cut efficiency map on the log\(_{10}(S2/S1)\) vs. \(S1\) distribution for the simulated accidental background.
Figure 12: The BDT cut efficiency curves as a function of $S_1$ and efficiency maps on the $\log_{10}(S_2/S_1)$ versus $S_1$ for different calibration data in the dark matter search window for different Runs.

Figure A.1: Distribution of the time difference between $S_{1,\text{max}}$ and $S_{2,\text{max}}$ at the condition where time difference between the isolated $S_1$ and $S_{1,\text{max}}$ is smaller than $120 \ \mu s$ ($\Delta t < 120 \ \mu s$) in method 3. The pink dashed line represents the maximum drift time.
Figure A.2: Accumulated charge pattern in the top PMT array of all isolated S1s from Mar. 11, 2018 to Apr. 6, 2018. Three PMTs are observed to have the largest contribution to these signals.

Figure A.3: Accumulated charge pattern in the top PMT array of isolated S1s in the window of (10, 12) PE in Run 11. Three PMTs are observed to have the largest contribution to these signals.
Figure A.4: The distributions of BDT response of the train and test data samples. The K-S test probabilities are used to indicate the overtraining.
Figure A.5: Correlations between the variables used for BDT training, from the events below the NR median.