

KamLAND-Zen 800 Status and Prospect with the Artificial Intelligence Powered Analysis

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Abstract. The discovery of neutrinoless double beta decay ($0\nu\beta\beta$) would shed light on the persistent puzzle surrounding the origin of neutrino mass and help explain the matter-dominated universe. KamLAND-Zen is one of the leading experiments searching for $0\nu\beta\beta$. The first phase of the experiment, called KamLAND-Zen 400, set a world-leading limit on $0\nu\beta\beta$ lifetime. After the conclusion of KamLAND-Zen 400, a brand new mini-balloon with a larger volume and cleaner surface were instrumented to contain 745 kg of ^{136}Xe . Since Jan. 2019, KamLAND-Zen 800 has started data-taking and aims to improve on the previous $0\nu\beta\beta$ result. A detailed study of the backgrounds in this new data will be presented along with a state-of-the-art approach for classifying backgrounds using a new algorithm called KamNet. The rejection power of KamNet does not rely on coincidence tagging and scales with hardware updates. With the help of KamNet, the $0\nu\beta\beta$ sensitivity of KamLAND-Zen 800 is significantly enhanced to a new summit.

1. Introduction

Neutrinoless double beta decay ($0\nu\beta\beta$) is one of the major research interests in neutrino physics. The discovery of $0\nu\beta\beta$ would prove the Majorana nature of neutrino [2], and further explain the extremely light neutrino mass through a seesaw mechanism [3, 4]. Moreover, $0\nu\beta\beta$ itself violates lepton number conservation. Thus, it could help explain the baryon asymmetry through a process known as leptogenesis[5]. The $0\nu\beta\beta$ decay rate is proportional to the square of effective neutrino mass. Given the mass differences of 3 neutrino mass eigenstates, the lightest neutrino mass can also be determined through a measurement of the decay rate. However, measuring the decay rate of $0\nu\beta\beta$ decay is a challenging task. It requires at least hundreds of kilograms of isotope that could undergo double beta decay, long exposures, and powerful background suppression techniques to achieve an environment that is nearly background free.

2. KamLAND-Zen

KamLAND-Zen deploys the $0\nu\beta\beta$ isotope, ^{136}Xe , inside the original KamLAND detector[6]. The isotope is loaded into liquid scintillator (LS), and the combination is usually referred to as Xe-LS. The Xe-LS fills a central nylon mini-balloon with a concentration of almost 3% by weight, and the isotopic abundance of ^{136}Xe is enriched to roughly 91%. The detector is located at a depth of 1,000 m (2,700 m.w.e), which reduces the cosmogenic muon rate to about 0.3 Hz. Xenon



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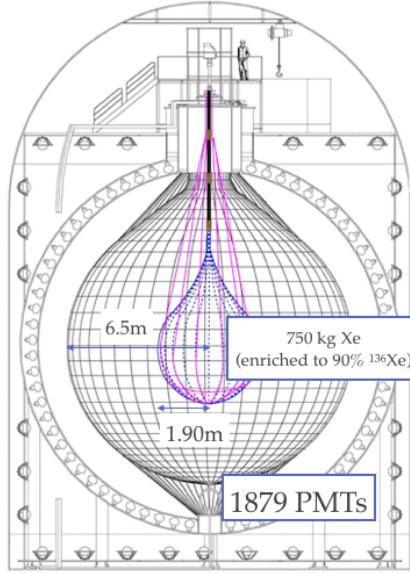


Figure 1: Illustration of the KamLAND-Zen detector configuration.

can be extracted from Xe-LS by vacuum and nitrogen bubbling, and purified by distillation and filtration. The inner balloon is surrounded by 1,000 tons of pure LS held in a 13-m-diameter outer balloon. The LS filling the outer balloon can also be purified by a multi-stage distillation system. Finally, the outermost region of the spherical detector contains mineral oil to quench undesired light on PMT surface. The full configuration of KamLAND-Zen detector is illustrated in Figure 1.

KamLAND-Zen has achieved $5 \times 10^{-18} \text{ g/g}$ and $1.3 \times 10^{-17} \text{ g/g}$ contamination level for ^{238}U and ^{232}Th , respectively[7]. This extremely low background environment is necessary in order to search for $0\nu\beta\beta$ decay. KamLAND-Zen is a phased program made up of the past KamLAND-Zen 400, the currently running KamLAND-Zen 800, and the future KamLAND2-Zen. KamLAND-Zen 400 finished data taking on October 2015 [8]. KamLAND-Zen 400 set a lower limit on ^{136}Xe $0\nu\beta\beta$ decay half-life at $T_{1/2} > 1.07 \times 10^{26}$ years at 90% C.L., corresponding to $\langle m_{\beta\beta} \rangle < 61 - 165 \text{ meV}$ [8]. The current project, KamLAND-Zen 800, started in 2015, and data acquisition started in January 2019. The first KamLAND-Zen 800 result had been released on TAUP 2019 with the ^{136}Xe $0\nu\beta\beta$ half-life limit of 4×10^{25} years at 90% upper confidence level[11]. A complimentary Bayesian analysis quotes 4.3×10^{25} years of half-life[10]. In the future, KamLAND2-Zen plans to use 1 ton of Xenon and would start in 2027. A major R&D effort to further reduce backgrounds is ongoing.

3. Long-Lived Spallation Backgrounds

Shortly after the release of the first KamLAND-Zen 800 result, we discovered another type of background that we did not consider in the TAUP 2019 result. When an incoming muon passes through the KamLAND-Zen 800 mini-balloon, the abundant ^{136}Xe nuclei will be spallated to produce radioactive isotopes with high mass numbers. As shown in Figure 2, those spallation products consist of β^\pm decay and leach into our region of interest. Typical spallation products are rejected with a triple coincidence tagging scheme:

- The muon track is reconstructed from outer detector PMT hits as the first coincidence

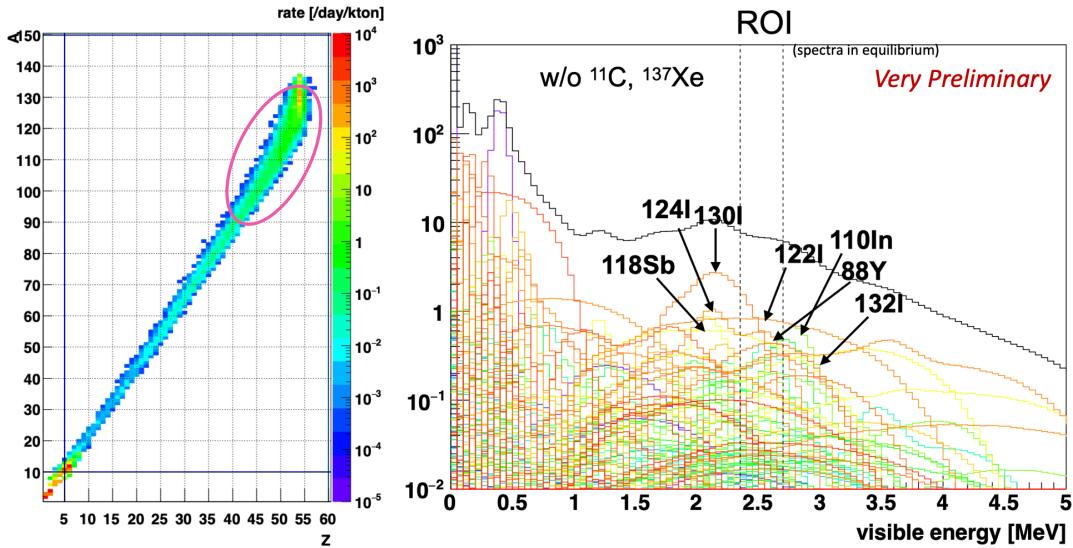


Figure 2: Illustration of the KamLAND-Zen detector configuration.

- Within certain distance (ΔL) and certain time window (Δt), tag the β^\pm decay of spallation product as the second coincidence. Δt is constrained by the half-life of spallation product
- Within certain radius (ΔR) of the second coincidence, search for the 2.2 MeV neutron capture γ event as the 3rd coincidence.

Triple coincidence tagging works well on short-lived spallation products such as ^{10}C decay. Unfortunately, most of the ^{136}Xe spallation products possess extremely long half-lives from hours to days. This significantly reduced our tagging efficiency of these spallation products since Δt need to be made very long. In traditional analysis, a triple coincidence long-lived spallation tag is made with large Δt to reject 40% of long-lived spallation events.

Suppose a particle identification (PID) technique can be invented to distinguish β^\pm decay from $0\nu\beta\beta$ signal event-by-event, the large Δt dilemma can be avoided since no coincidence will be used. However, non-coincidence PID is a highly challenging goal for liquid scintillator detectors. It requires us to obtain tracking and topology information - traditionally exclusive for tracker detectors - on a calorimeter detector. To achieve this challenging goal, we must leverage the supremacy of artificial intelligence to extract every single bit of information from data.

4. KamNet: The State-of-the-Art Neural Network

The power of conventional convolutional neural network (CNN) to suppress cosmic muon spallation backgrounds have been demonstrated in our previous work [9]. However, with a simple interpretability study, we found that conventional CNN only harnesses temporal symmetry. In other words, it only attempts to reject background based on scintillation time profile instead of the full event topology. This greatly constrains the performance of the neural-network-based model on the rejection performance of cosmic muon spallation backgrounds. To remedy this, we invented a novel deep learning model - KamNet.

KamNet is a state-of-the-art machine learning algorithm that harnesses the symmetry of a spherical detector to discriminate between topological differences in energy deposits and is now being used to separate the $0\nu\beta\beta$ signal from other types of events in KamLAND-Zen. As shown in Figure 3a, each KamLAND-Zen 800 event is first pre-processed into a series of 2D PMT hit

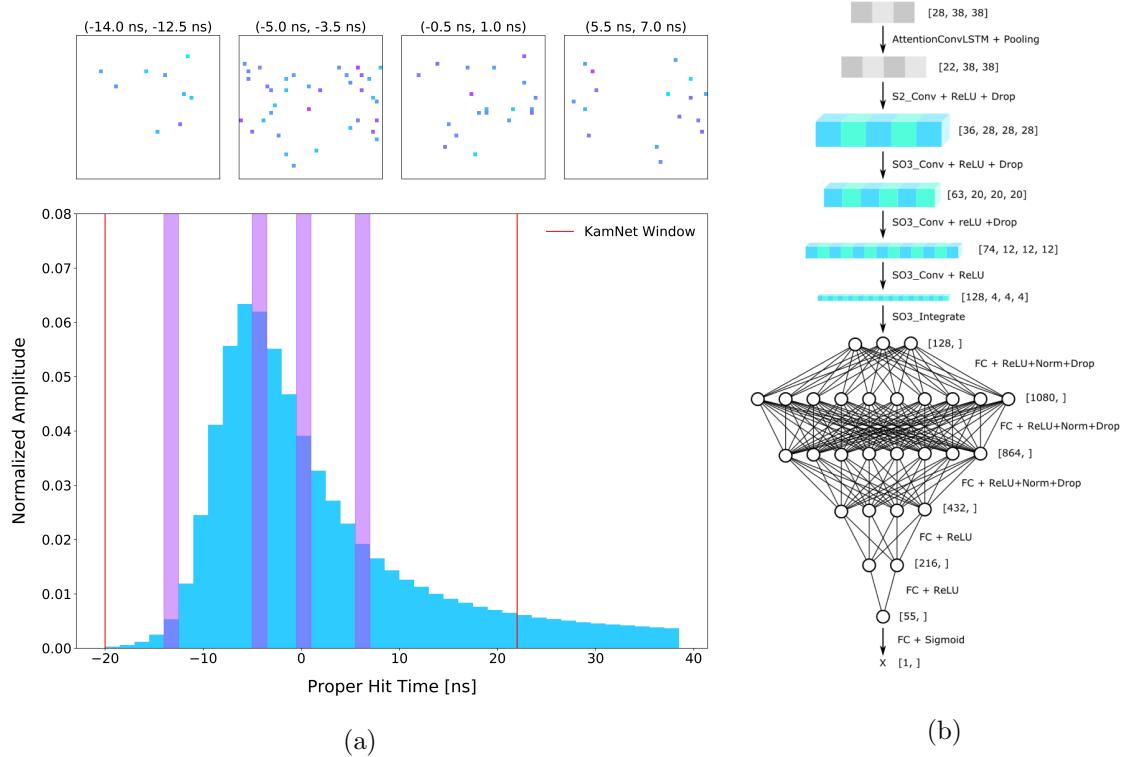


Figure 3: (a) Demonstration of the scintillation time profile of KamLAND-Zen events and corresponding 2D hit maps at different time indices. (b) Diagram of KamNet.

maps by opening up the sphere. The hit map series are then fed into KamNet in Figure 3b for training and validation. Three frontier machine learning models inspire KamNet's architecture:

- ConvLSTM [12] to harness spatiotemporal symmetries among triggered PMTs at different time
- Attention mechanism [13] to zoom in to the scintillation peak and provide interpretability via attention score
- Spherical CNN [14] to harness spherical symmetry arising from spherical detector topology

By harnessing all symmetries in data, KamNet captures the subtle difference between strictly single vertex signal events and closely spaced multi-vertex events in a spherical detector. This powerful model allows the rejection of background without any coincidence tagging or hardware upgrade. An excellent data-MC agreement is also reached by studying the ^{214}Bi backgrounds.

Figure 4 showed the rejection performance of KamNet evaluated on Monte-Carlo simulations. While accepting 90% $0\nu\beta\beta$ events, KamNet rejects about 30% of XeLS backgrounds (including LL spallation) and about 60% of mini-balloon film backgrounds. The rejection power comes from the topology and PMT hit times of single events rather than coincidence-tagging between events. Therefore, KamNet's rejection power is multiplicative with the existing LL coincidence tag. Furthermore, The increased rejection of backgrounds on mini-balloon film allows for expanding the fiducial volume from 157cm to 165.8cm, resulting in 17.7% gain on exposure without increasing film backgrounds.

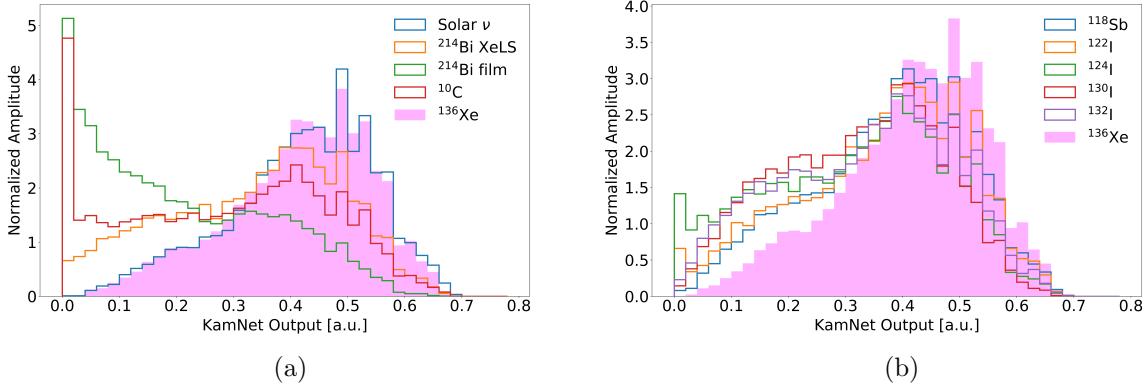


Figure 4: (a) KamNet classification output for solar neutrino, ^{214}Bi , and ^{10}C backgrounds (b) KamNet classification output for dominant long-lived spallation backgrounds. All histograms have been normalized to unity.

5. Conclusion

$0\nu\beta\beta$ is one of the major physics goals in neutrino physics, and the KamLAND-Zen experiment is one of the leading efforts in search of $0\nu\beta\beta$ decay. The current phase, KamLAND-Zen 800, had started data-taking on Jan. 2019, and preliminary fitting results from TAUP 2019 indicate an upper limit (90% C.L.) of 4×10^{25} yrs on $0\nu\beta\beta$ half-life of ^{136}Xe . Shortly after the TAUP 2019 result, we discovered the long-lived spallation product of ^{136}Xe nuclei, which then became the major background in our ROI. KamNet was invented to reject these backgrounds without coincidence tagging or hardware updates. While accepting 90% $0\nu\beta\beta$ events, KamNet rejects about 30% of XeLS backgrounds (including LL spallation) and about 60% of mini-balloon film backgrounds. With the help of KamNet, the $0\nu\beta\beta$ sensitivity of KamLAND-Zen 800 is significantly enhanced to a new summit.

References

- [1] Gando, Y. (2019, September). First results of KamLAND-Zen 800. Oral presentation at Topics of Astroparticle and Underground Physics(TAUP) 2019, Toyama, Japan.
- [2] J. Schechter and J. W. F. Valle, *Phys. Rev. D*, **25**, 774783 (Feb 1982).
- [3] T. Yanagida, in *Proceedings of the workshop on Unified Theory and Baryon Number of the Universe*, eds. O.Sawada and A.Sugamoto (KEK) p.95.
- [4] M.Gell-Mann, P.ramond and R.Slansky, in *Supergravity*, eds. P.van Niewwen-huizen and D.Freedman (North holland, Amsterdam) (1979).
- [5] M. Fukugita, T. Yanagida, *Phys. Lett.* **B174** (1986) 4547.
- [6] K. Eguchi et al. (KamLAND Collaboration), *Phys. Rev. Lett.* **90** 021802 (2003)
- [7] A.Gando et al. (KamLAND Collaboration) *Phys. Rev. C* **92**, 055808 (2015).
- [8] A.Gando et al. (KamLANDZen Collaboration), *Phys. Rev. Lett.* **117** 082503 (2016).
- [9] A. Li, A. Elagin, S. Fraker, C. Grant and L. Winslow, doi:10.1016/j.nima.2019.162604 arXiv:1812.02906 [physics.ins-det].
- [10] A. Li [KamLAND-Zen], *J. Phys. Conf. Ser.* **1468**, no.1, 012201 (2020) doi:10.1088/1742-6596/1468/1/012201
- [11] Y. Gando [KamLAND-Zen], *J. Phys. Conf. Ser.* **1468**, no.1, 012142 (2020) doi:10.1088/1742-6596/1468/1/012142
- [12] Xingjian, S. H. I., et al. "Convolutional LSTM network: A machine learning approach for precipitation nowcasting." *Advances in neural information processing systems*. 2015.
- [13] Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." arXiv preprint arXiv:1409.0473 (2014).
- [14] Cohen, Taco S., et al. "Spherical cnns." arXiv preprint arXiv:1801.10130 (2018).