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ELEMENTARY PARTICLES AND FIELDS
Experiment

Determination of Dead Layer Parameters of Semiconductor Germanium Detectors Using Machine Learning for the Legend Experiment

N. Levashko[1)*], A. Alexander[2)], V. Biancacci[3),4)], A. Chernogorov[1)], and A. Li[5),6)]

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Abstract—The search for neutrinoless double-beta decay remains today one of the most important areas in particle and nuclear physics. Germanium detectors are an excellent technology for this search because of their state-of-the-art energy resolution, but a dead layer in a germanium crystal can reduce the active volume, which can affect both exposure and half-life sensitivity. In this work, we used machine learning methods to study the dead layer in enriched germanium crystals. 1000 sets of events were simulated with various combinations of dead layer parameters. A fully connected neural network was used to determine these parameters from the energy spectra of a germanium detector exposed to a gamma calibration source Barium-133.

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1. DOUBLE NEUTRINOLESS BETA-DECAY

Neutrinoless double-beta decay (Fig. 1) is a hypothetical nuclear decay that has never been observed. Its observation would signal that the lepton number is not conserved and that the neutrinos are Majorana particles. In addition, it could confirm the expected absolute neutrino mass scale at the level of several tens of meV [1].

2. LEGEND-200 EXPERIMENT

The LEGEND-200 [2] experiment will operate 200 kg of Ge detectors in a bath of liquid argon (LAr) in an upgrade of the GERDA [3] infrastructure at LNGS. The LEGEND-200 design combines the best elements of GERDA and the Majorana Demonstrator [4]. Until the experiment's next phase—LEGEND-1000 [5], LEGEND-200 will be one of the leading experiments in the field, reaching a half-life sensitivity of 10^{27} yr after five years of operation. Schematically, the detector is shown in Fig. 2.

1) National Research Center "Kurchatov Institute", Moscow, Russia.
2) University College London, London, United Kingdom.
3) Dipartimento di Fisica e Astronomia dell'Universita' di Padova, Padova, Italy.
4) Padova Istituto Nazionale di Fisica Nucleare, Padova, Italy.
5) Department of Physics and Astronomy, University of North Carolina, USA.
6) Triangle Universities Nuclear Laboratory, Durham, USA.
* E-mail: nikstar2010@mail.ru

3. HIGH PURITY GERMANIUM DETECTORS

Germanium detectors are used in the LEGEND experiment for a number of reasons: Excellent energy resolution—0.1% at $Q_{\beta\beta} = 2039$ keV, practically radio-pure, both a detector element and a source and enrichment at the level $> 90\%$ is possible. The innovative Inverted Coaxial Point Contact (ICPC) design will be one of the main detector geometries used for LEGEND since they possess a larger mass (> 2 kg) than previous point contact detectors while preserving good energy resolution. Figure 3 shows several types of germanium detectors used in the experiment, including BEGe and semi-coaxial detectors. BEGe—Broad Energy Germanium Detector, is good for pulse shape discrimination of signal against background. The semi-coaxial detector is larger than the BEGe, resulting in a larger active mass. P-type point contact (PPC) detectors are not shown in the figure, but they are also used in the experiment.

4. FULL CHARGE COLLECTION DEPTH MODEL

The Full Charge Collection Depth (FCCD) is an important characteristic of the detector, since it completely determines the active volume. It indicates the distance from the edge of the detector through which the charge collection efficiency is 1. In our study, we used a simplified FCCD model (Fig. 4):

- Full Charge Collection Depth = Dead Layer + Transition Layer.
- Dead Layer (DL) = region of no charge collection on surface of semiconductor detectors.

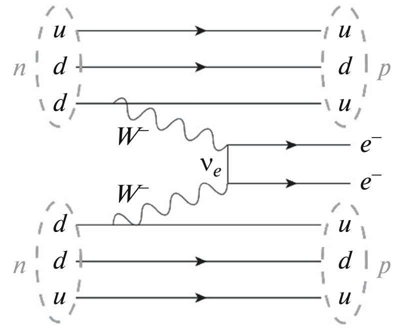

Fig. 1. Feynman diagram of the neutrinoless double-beta decay process.

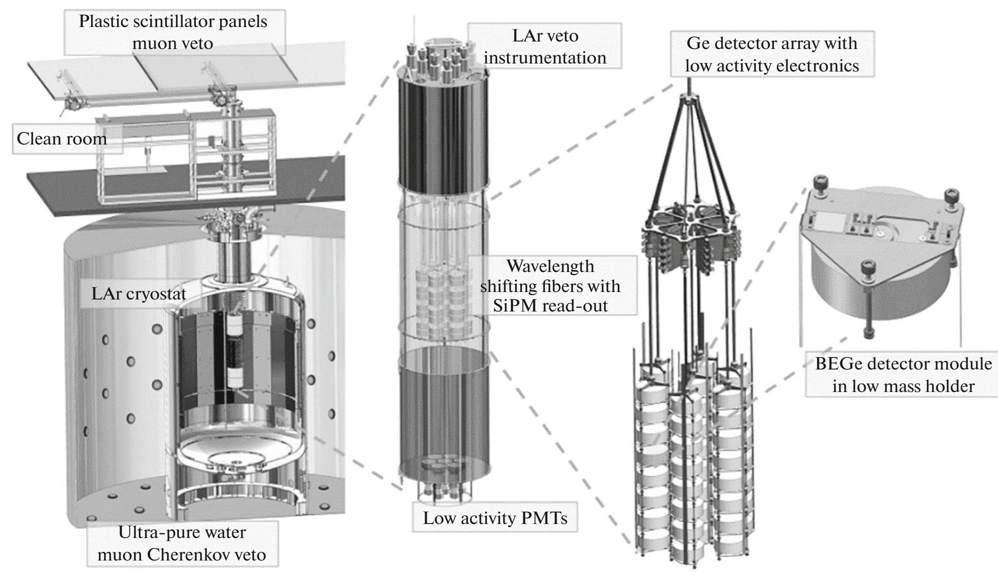

Fig. 2. Schematic representation of the LEGEND-200 experiment. The germanium detectors are deployed into the LAr cryostat in strings, surrounded by the LAr veto instrumentation. The cryostat itself is located inside the water tanker for protection from muons.

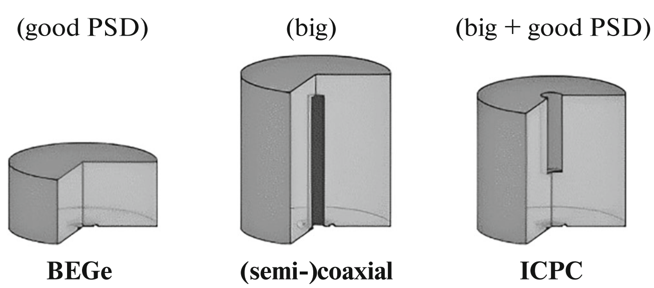

Fig. 3. Image of germanium detectors used in the experiment. BEGe—Broad Energy Germanium Detectors, the semi-coaxial detector and ICPC—Inverted Coaxial Point Contact detector.

- Transition Layer (TL) = partial charge collection, here modelled with linear function, although other functional forms are possible.

The determination of the FCCD is important because the half-life of $0\nu\beta\beta$ is dependent on the active mass, as are the constraints on the mass of the neutrino. In addition, degraded events (where part of the energy is deposited in the dead layer) can mimic the $0\nu\beta\beta$ signature and make event analysis even more difficult.

5. NEURAL NETWORKS

A neural network is a machine learning model that uses interconnected nodes or neurons in a layered

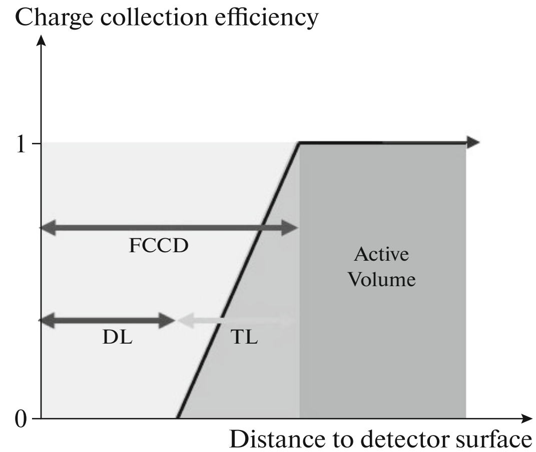

Fig. 4. Graphical depiction of the used full charge collection depth model used in this work. The area where charge collection is completely absent is the dead layer (DL). The region with partial charge collection is the transition layer (TL). The charge collection efficiency increases linearly from 0 to 1 as it approaches the active volume (AV).

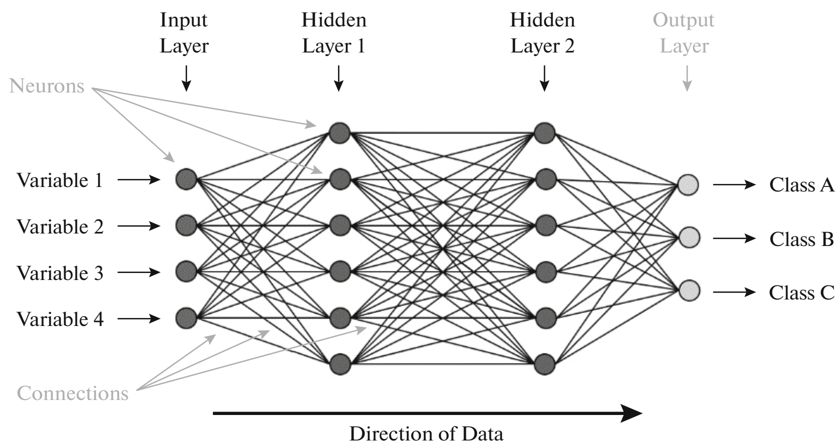

Fig. 5. Visual representation of the used neural network. The network consists of several layers. The available information, for example, the energy spectrum, is fed to the input layer. Then it enters the hidden layers, where it is transformed according to the weights of the neurons. The resulting transformed data is sent to the output layer through the hidden layers. From the output layer, we get the data we need.

structure that resembles the human brain. The basic neural network contains three layers of connecting artificial neurons: input layer, hidden layers and output layer (Fig. 5). The input layer is fed with the available data. The input nodes process the data, analyze or classify it, and pass it on to the next layer. As a rule, the data must first be prepared. Hidden input layers receive data from the input layer or other hidden layers. Artificial neural networks can have a large number of hidden layers. Each hidden layer parses the output of the layer collection, collects it, and passes it on to the next layer. The output layer is the secondary result of processing all the data of the artificial neural network. It may have one or more nodes. For example, when solving a binary classification problem (yes/no), the output layer will have one output node, which will give the result “1” or “0”. However, in the case of multiple classifications, the output layer may consist of more than one output node.

There are also more complex variants of neural networks [6], but in our work we decided to focus on a fully connected neural network.

6. PROCEDURE

To determine the parameters of the dead layer, it is necessary to prepare data for training the neural network. Monte Carlo simulations of ICPC detector exposed to Ba-133 in the HADES [7] underground laboratory were prepared with a different set of values for two determined parameters—FCCD and Dead Layer Fraction (DLF), where DLF = DL/FCCD for

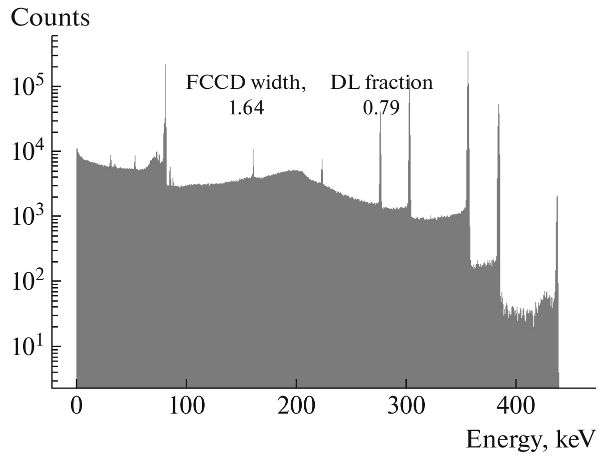

Fig. 6. An example of input data for a neural network. The data is an energy spectrum of ^{133}Ba in the range from 0 to 450 keV with a bin width of 0.5 keV—an array of 900 values, where each value indicates the number of events that fell into this bin.

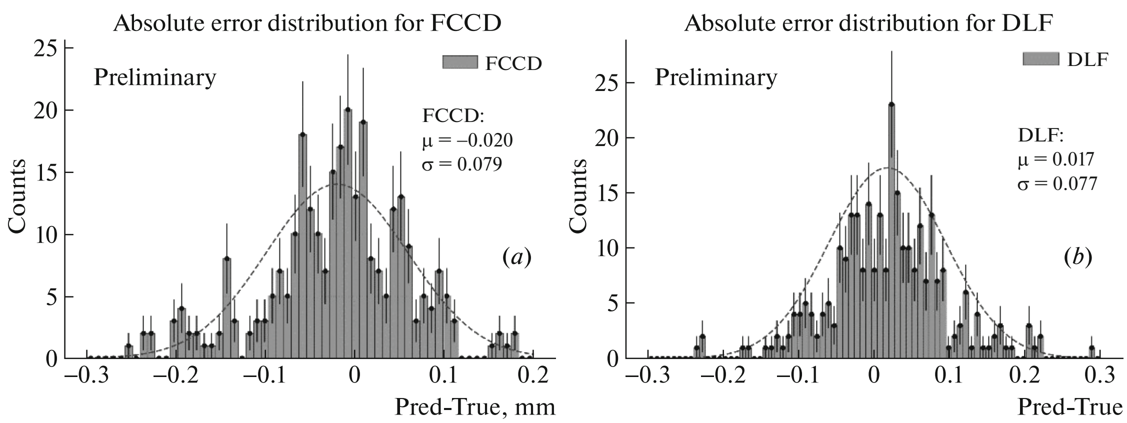

Fig. 7. Plots of absolute error distribution in the determination of parameters. (*a*) for FCCD parameter, (*b*) for DLF parameter.

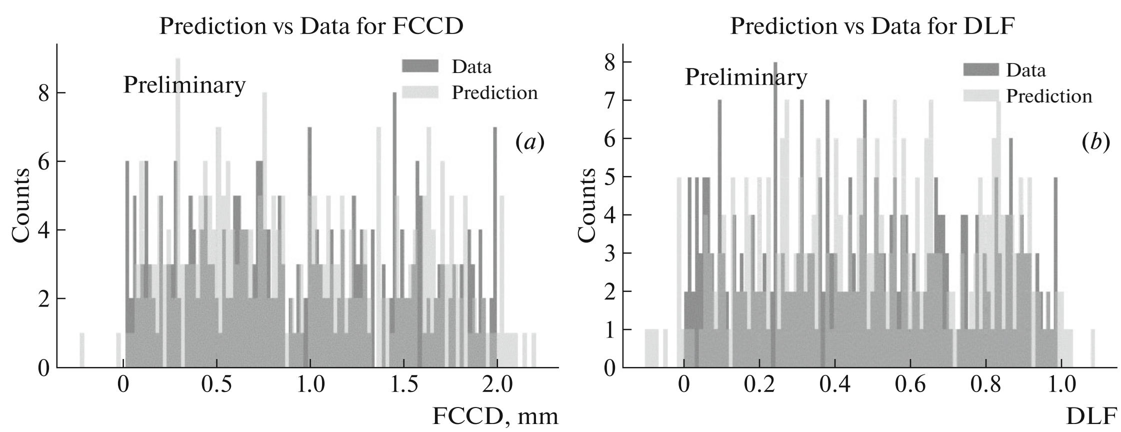

Fig. 8. Distribution plots of predicted parameter values along with true values. (*a*) for FCCD parameter, (*b*) for DLF parameter. Dark gray defines data, light gray—prediction, medium gray—their superposition.

a linear TL model. A total of 1000 random combinations of FCCD and DLF were generated and the training was carried out on 700 of these files. A fully connected neural network with 4 layers was used. The results of training the neural network were tested on the remaining 300. Figure 6 shows a sample of the data on which the neural network was trained.

7. PRELIMINARY RESULTS

The resulting plots, in particular plots of absolute errors in parameter determination (FCCD and DLF) and distribution plots of predicted parameter values along with true values are presented in Fig. 7 and Fig. 8, respectively. The absolute error distribution for both parameters was fitted with a Gaussian function. The obtained distribution parameters are shown in the plots. With the use of a simplified FCCD model and a fully connected neural network, it was possible to achieve an accuracy of about 0.1 mm in determining FCCD. The obtained accuracy coincides in order of magnitude with the values obtained in the study of the characteristics of germanium detectors in other works [8, 9]. The next step is to use a more complex neural network and increase accuracy and eventually test the network on real data taken with the germanium detector.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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