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FINAL REPORT

Design and Optimization of a Radioisotope Identification Code for use in Gamma-Ray Detectors

Prepared for

NUCL450 SENIOR DESIGN

by

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Purdue University | Nuclear Engineering, College of Engineering

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Secondly, we would like to thank Dr. Shripad Revankar and the School of Nuclear Engineering for supporting us through these projects and facilitating the connection of students with outstanding companies in the field of Nuclear Engineering.

Lastly, we would like to thank True Miller for his time and effort in helping us to understand and be able to use MCNP.

TABLE OF CONTENTS

ABSTRACT

With the growing threat of nuclear waste and the ease of transport of nuclear materials, the need for real-time detection and identification of radionuclides is becoming increasingly urgent. To address this challenge, Team H3D proposes to develop a Python algorithm that can detect and identify radioisotopes in real-time by utilizing the Monte Carlo N-Particle Transport Code (MCNP) to generate various radionuclide gamma-ray spectra. The algorithm will be tested against unknown spectra and can be integrated into detectors to support nuclear power, waste management, nuclear nonproliferation, and medical applications. This report provides a comprehensive review of previous research in this field, outlines the usage of MCNP, and concludes with our plan of action.

EXECUTIVE SUMMARY.

The aim of this project is to develop and improve a radioisotope recognition program for gamma ray detector devices. This will be achieved through the construction of a Python code that can identify radioisotopes based on their gamma spectra. The program will use a sample of gamma ray emitters that have been approved and verified by the ANSI organization. To ensure success, we will follow the design criteria set by ANSI and aim to exceed their standards. This criteria includes an isotope library, testing procedures, and mechanisms that must be adhered to for the project to be validated. The ultimate goal of this project is to provide a reliable and accurate radioisotope recognition program that can be integrated into gamma ray detector devices for various applications.

CHAPTER 1. LITERATURE REVIEW

Multiple technical papers were given to our team to review before we began to work. These papers would inform us as we began the process of developing a strategy to tackle this problem.

1.1 C.C. Conti et al. "A detailed procedure to simulate an HPGe detector with MCNP5" [2]

This paper was published by a group who were able to model a High-Purity Germanium gamma-ray detector using MCNP5. This was a very important paper for our group to understand because using MCNP is integral to the completion of our project.

In the paper, C. C. Conti and his team lay out how they wrote the data cards for the HPGe detector. These data cards have a very important syntax, so this paper was important for us to be able to have examples to follow in modeling using MCNP.

1.2 ANSI N42.34: "American National Standard Performance Criteria for Handheld Instruments for the Detection and Identification of Radionuclides." [1]

The American National Standards Institute (ANSI) is a private, non-profit organization that develops standards for the US' voluntary standards program, a collaboration between industry, government, and consumer groups that agree on best consumer product safety standards.

ANSI N42.34 is the document that lays out the standards and performance criteria that radioisotope identification devices (RIDs) are held to. The specifications for many types of performance including radiological, electromagnetic, and mechanical are included in the document. THere are 4 types of gamma-ray detectors that are governed by the standards, Sodium Iodide (NaI), Cadmium-Zinc-Telluride (CZT), High-Purity Germanium (HPGe), and Helium-3 (He-3). For our project we will only be focusing on NaI, CZT, and HPGe.

The most important parts of this standards document are the radiological performance standards for the RIDs. This section lays out how an RID must perform when it is detecting and identifying a radionuclide. The RID must be able to detect and identify a list of radionuclides, shown below, with an exposure rate of no more than 50 μR/h (micro-Roentgen per hour). The measurement and identification shall happen in 2 minutes. This can lead to “count-starved” data, which is when the data recorded isn’t enough to identify with a high level of certainty.

1.3 J. K. Shultis, Kansas State University: “An MCNP Primer” [4]

An MCNP Primer is a paper published by two professors in the Departments of Mechanical and Nuclear Engineering at Kansas State University, J. K. Shultis and R. E. Faw. Their paper condenses the well known MCNP Manual, which is distributed by Oak Ridge National Laboratory, and defines how to use MCNP. This paper is another important source for our group to learn from because it shows us how to model everything in MCNP. The HPGe research paper shows us how to model an HPGe detector, but we still need to be able to effectively model the NaI and CZT detectors.

This paper is also important because it will teach us the correct way to format the output of MCNP so that it can be of use to us. The end goal of using MCNP is to be able to output gamma-ray spectra, then write a code to read those spectra.

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CHAPTER 2. PROJECT FOUNDATION

Background:

The detection of gamma rays relies on transfer of their energy to electrons and measurement of the ionization created as the high-energy electrons move through matter. Gamma-ray detectors can perform the difficult task of gamma-ray imaging. For this project there will be three main radionuclide isotope detectors that our MCNP code will serve one being a scintillation type detector of Sodium Iodide composition (NaI) and two semiconductor type detectors, High Purity Germanium (HPGe), and a Cadmium Telluride Zinc (CZT) Detector. The exact detector material composition and dimensions have been instituted by the sponsor for us which is shown in the following:

CZT

- 50% Cadmium, 10% Zinc, 40% Telluride
- Rectangular Parallelepiped (40 x 40 x 8 mm)

NaI (Tl)

- 49.95% Sodium, 49.95% Iodine, 0.1% Thalium
- Cylinder (50.8 x 50.8 mm, D x H)

HPGe

- 100% Germanium
- Cylinder (65 x 50 mm, D x H)

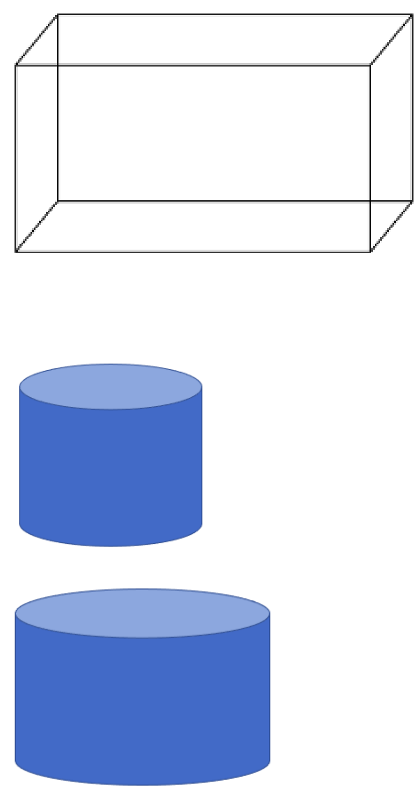


Figure 1. Representations of detecting media

The spectrum detected will have features and characteristics that the radionuclide isotope detector and MCNP code can recognize. The most important features are backscatter peaks, photopeaks, Compton Plateau, Compton Edge, single and double escapes. Background and electrical noise that appear in the collection of data will have to be segregated from areas of interest. A sample spectrum is shown below:

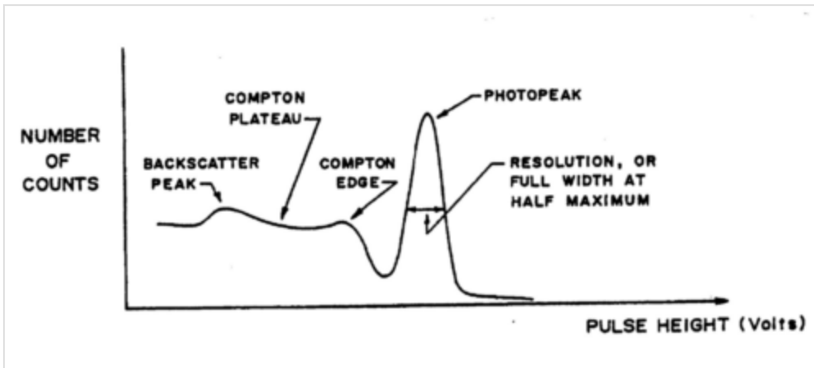


Figure 2. Example of gamma-ray spectrum

Each type of detector possesses unique features that differentiates itself from another. The most significant factors include resolution, efficiency, precision, electron-hole pairs generation energy, and operating conditions of the radionuclide isotope detector. Gamma rays detected in a spectroscopic system produce peaks in the spectrum. The width of the peaks is determined by the resolution of the detector. High resolution enables the spectroscopist to separate two gamma lines that are close to each other. Gamma spectroscopy systems are designed and adjusted to produce symmetrical peaks of the best resolution possible. The peak shape is usually a Gaussian distribution. In most spectra the horizontal position of the peak is determined by the energies of gamma rays. The area of the peak is determined by the intensity of the gamma ray and the efficiency of the detector. High-efficiency detectors will produce spectra faster than low-efficiency detectors. In general, larger detectors have higher efficiency than smaller detectors, although the shielding properties of the detector material are also important factors. Detector efficiency is measured by comparing a spectrum from a source of known activity to the count rates in each peak to the count rates expected from the known intensities of each gamma ray [6]. The operating conditions refers to the condition that the detector must be within in order to function normally. For instance the HPGe detector must operate at cryogenic temperature using liquid nitrogen to produce an accurate spectrum. This is unlike other types of detectors that can operate at room temperature. As for the electron-hole pairs generation energy, an electric field is applied to the detector volume. Using semiconductor detectors as an example, an electron in the semiconductor is fixed in its valence band in the crystal until a gamma ray interaction provides the electron enough energy to move to the conduction band. Electrons in the conduction band can respond to the electric field in the detector, and therefore move to the positive contact that is creating the electrical field. The gap created by the moving electron is called a "hole", and is filled by an adjacent electron. This shuffling of holes effectively moves a positive charge to the negative contact. The arrival of the electron at the positive contact and the hole at the negative contact produces the electrical signal that is sent to the signal analyzing trip in detectors, which in return produces the desired spectrum at the end that is analyzed by the MCNP code to identify the radionuclide isotope [6].

Importance:

This project serves the scientific industry in many ways that are of real life application and has proved this in several fields. It enables the development of real-time radiation detection and localization that is used in nuclear power plants, contaminated facilities, long and short term waste storages, defense and homeland security, healthcare facilities, nuclear forensics, and has also been under testing for space applications. Gamma-ray imaging has been used in nuclear power plants in site surveys, shipping inspections, shield testing, and helps meet safety regulations and requirements while providing useful information on radiation quantifications.

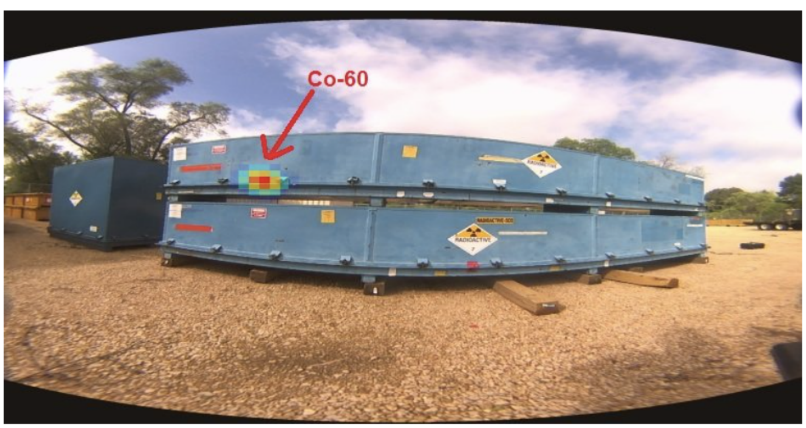


Figure 3. Image showcasing and H3D detector’s imaging and localization capabilities [10]

The detectors have been used in Defense and Homeland security, in helping interdiction in stadiums or high population events by monitoring people and objects for threats, assessing threat levels by determining the presence of highly dense radiation or dirty bomb, navigating of high intensity sources by directional mechanisms and localizing radiation.

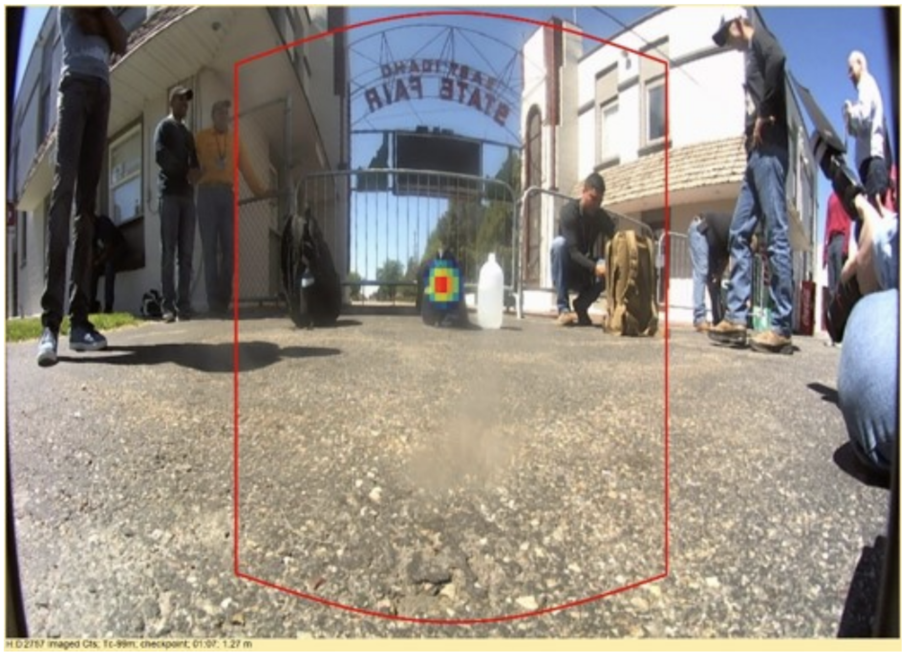


Figure 4. Image showcasing and H3D detector’s imaging and localization capabilities [10]

In nuclear forensics, by quantifying the radiation detected researchers can determine the age of isotopes using analytical techniques to determine the origin and history of materials in the context of law enforcement investigations or the assessment of nuclear security vulnerabilities. While this is not of recent history, medical usage of gamma ray detectors is still under development and optimization, although the technology is still available. Additionally, CZT detectors have been undergoing testing by NASA for space applications recently.

CHAPTER 3. Design Criteria

The design criteria for this project will be dependent on the American National Standard Institute (ANSI) N42.34 Standards. The ANSI provides an isotope library that the radioisotope detector should be able to detect as a minimum:

Table 1. ANSI N42.34 required isotope library [1]

^{241}Am	^{137}Cs	^{40}K	^{232}Th	DU
^{133}Ba	^{67}Ga	^{99m}Tc	^{235}U	HEU
^{57}Co	^{131}I	^{201}Tl	^{238}U	WGPu
^{60}Co	^{192}Ir	^{226}Ra	^{239}Pu	RGPu

The ASNI has set certain requirements for testing of single radionuclide identification. An radioisotope detector shall be able to identify the radionuclides listed in Table 3 at an exposure rate of 50 μR/h above background established at the reference point of the radioisotope detector within an integration time of 2 minutes or that stated by the manufacturer, whichever is shorter. The test method to determine whether the radioisotope detector meets the single radionuclide identification requirements is as follows (ANSI):

1. Position the reference point of the RID 1m from the floor or ground surface.
2. According to the manufacturer's instructions, set up the RID to perform fixed object or static measurements. This may require the user to perform some action to manually initiate a measurement.
3. Position the 241Am source from Table 3 at the source to reference position distance needed to produce 50 μR/h above background (see 6.1.4).
4. Initiate a measurement for the specified static measurement time.
5. At the end of the measurement, record the identification results and the confidence indicator(s).
6. Without moving the source, repeat the process stated in step 4) and step 5) for a total of 10 trials.

The confidence indicator is based on an acceptance range based on the mean value and standard deviation derived from a series of measurements (e.g., count rate, exposure rate). The range is typically ±15% adjusted to compensate for the standard deviation determined at nominal conditions. The following process is used to determine the acceptance range:

1) Position the test source(s) as required and collect 10 readings without moving the source(s). There should be a minimum of three update intervals between each reading enabling each reading to be independent.

2) Calculate and record the mean response and experimental standard deviation for the series of readings.

3) Use the following equation to calculate the 95% confidence interval (CI) for a sample size of n.

$$CI_n^{95\%} = t_n \times \frac{s}{\sqrt{n}}$$

where,

- tn is the two-sided Student's t value for 95% confidence interval for a sample size of 10 (t_{10} = 2.26)
- s is the experimental standard deviation for the series of measurements
- n is the number of measurements (n = 10)

4) Multiply the mean value by 15% and then add the value $CI_n^{95\%}$.

5) Add the value from step 4) to the mean value to establish the upper limit and subtract the value from step 4) from the mean value to establish the lower limit. The upper and lower limits establish the acceptance range.

CHAPTER 4. ENGINEERING DESIGN PROCESS

The engineering design approach has been and will be incorporated into this project by Team H3D. This process has helped maintain an effective schedule and will continue to do so while ensuring that the final product is developed successfully and in accordance with sponsor requirements. The engineering design process can be divided into several key categories, which include: defining the problem, outlining potential solutions, gathering information and outlining options, specifying constraints, taking into account alternate solutions, choosing a course of action, developing a written design proposal, creating the model, testing and evaluating it, improving it, developing the product, and communicating the findings. The graphic below summarizes these categories and the order in which they are finished.

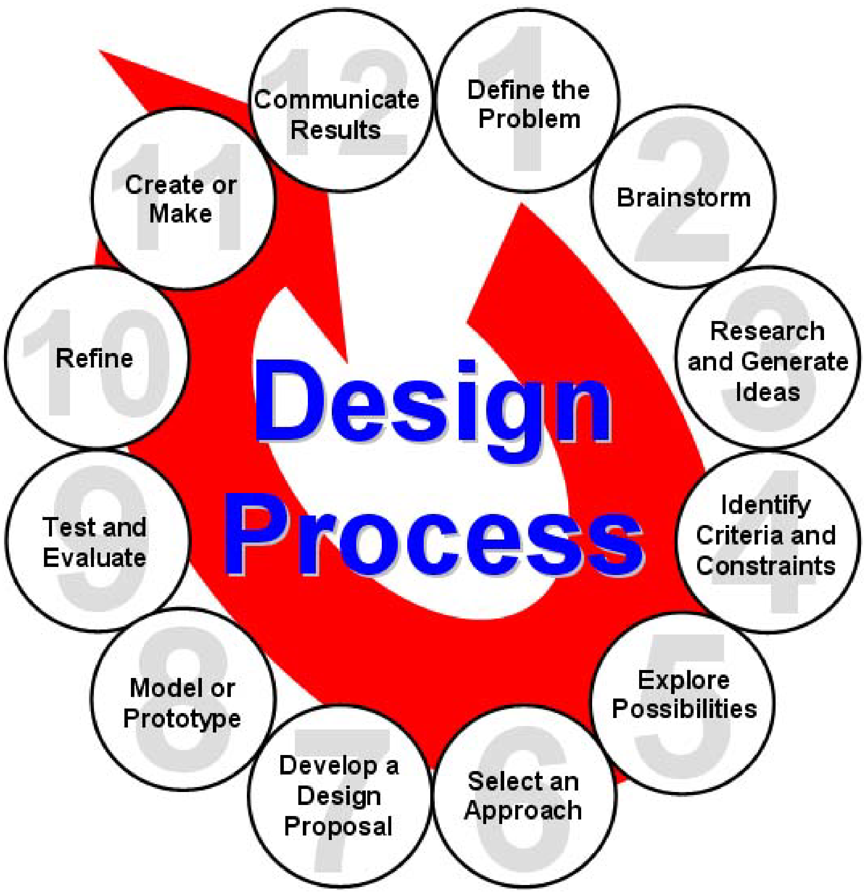


Figure 5. Engineering design process

The "Develop Written Design Proposal" stage includes this design proposal. Team H3D has finished all the categories prior to this stage. Plans have been made to finish the remaining categories in the design process.

The Engineering Design Process was started by Team H3D by first defining the problem. The issue that Team H3D intends to address is the growing demand for real-time radionuclide detection and identification capabilities. As was already mentioned, as nuclear waste production increases, efforts are being made to improve radiation detection. The development of real-time radiation localization, which is used in nuclear power plants, contaminated facilities, long- and short-term waste storages, defense and homeland security, healthcare facilities, nuclear forensics, and has also been tested for space applications, can be improved with increased radiation detection. In nuclear power plants, gamma-ray imaging has been utilized for site assessments, ship inspections, shield testing, and for helping to meet safety standards and requirements while providing helpful data on radiation quantifications.

The problem was examined and potential remedies were investigated. The majority of the solutions were simulation-based. Although there may be experimental solutions, Team H3D decided against it because of the scope of the problem, the expenses involved, and the lack of equipment. As a result, it was decided that the best way to solve the problem was to simulate the detectors, feed isotope input repeatedly, and analyze the outcomes accordingly.

The next action Team H3D took was the investigation of different ideas and exploration of possible avenues. The primary method used for this was a literature review. "A detailed procedure to simulate an HPGe detector with MCNP5", ANSI N42.34, and the MCNP Primer released by Kansas State University were the key pieces of material that Team H3D examined. The literature provided insight into prospective parameters and modeling techniques, as well as comprehension of the current challenge. These pieces of literature provided information about the performance requirements and standards that radioisotope identification devices (RIDs) must meet, which take into account information gathered by various groups and organizations. These literature pieces also discussed some essential elements that were important to our simulation interests, such as the material, the outside forces to take into account, and the tally. Team H3D additionally read material related to how to simulate these conditions in addition to these pieces of literature. Team H3D specifically looked over the MCNP Manual. This document included all relevant details for the suggested simulation approach, including different scenarios to represent the source in.

The process of defining limitations and choosing criteria relevant to our issue and solution was then started by Team H3D. Several important restrictions and requirements were discovered through the literature review and discussions with Team H3D representatives. It is possible to think of the identified criteria as generalized parameters that Team H3D would need to take into account and apply when developing the solution. These requirements include making sure the solution complies with ANSI standards. The detector types, material composition and size, availability of MCNP, spectral resolution, time-constrained data collection, and time are some of the constraints that Team H3D discovered.

The process of choosing a strategy for creating a solution to the presented problem was then started by Team H3D. In addition, Team H3D chose a method for effectively resolving the issue. Team H3D created a Gantt Chart to solve the time and programming restrictions. This proposal's following sections go into more detail about the Gantt Chart.

CHAPTER 5. MCNP MODELLING

The MCNP modeling began with a familiarization of MCNP using various sources, including the supplied MCNP User Manual as well as research papers and projects. Throughout the early stages of this, the problem we would be modeling became more clear. We simplified the problem by making several assumptions. Firstly, we modeled a point isotropic source, 1 meter from the detector, and, to save computational power, we collimated all particles emitted into a cone directed at the detector. Secondly, we modeled the detectors with very simple geometries, assuming only one layer of aluminum around the detector. Although not completely accurate with the detectors in real-life, it was sufficient to be able to generate simulated data for our code. A depiction of our model is shown below.

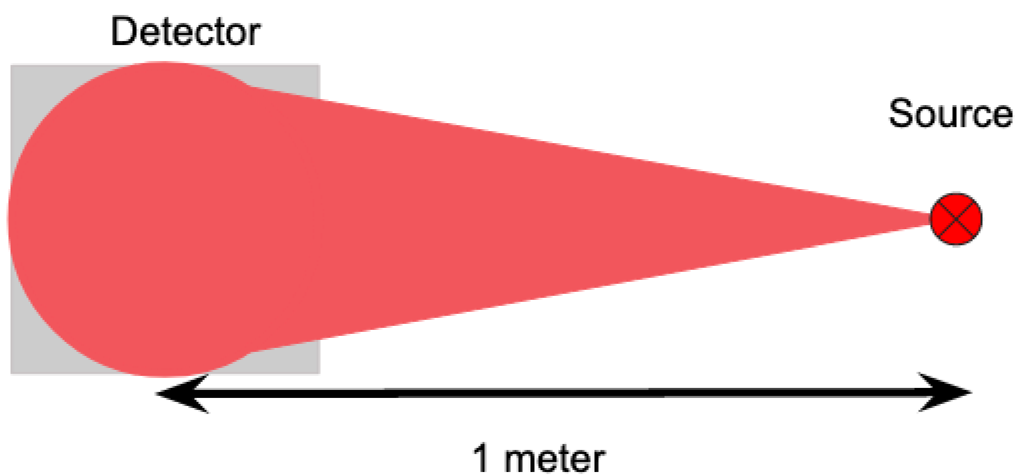


Figure 6. Image depicting MCNP model

The second step to modeling using MCNP was developing a radioisotope library with specifications for each radioisotope. The specifications needed were the gamma-ray energies that corresponded to each isotope, as well as the probability of emission of each gamma-ray. This was important not only for the MCNP source specification, but also for use in the coding part of the project, where this library would be used to specify locations in spectra to look for peaks. This isotope library was compiled by referencing the gamma-ray spectroscopy catalog, which is a source of many radioisotope spectra that have all of the gamma energy and probabilities displayed. To simplify the problem, we neglected to add gamma-rays that had low probabilities relative to other gamma-rays in the spectra. Also, in the case of Plutonium, we referenced a research paper from Lawrence Livermore National Laboratory that studied rapid, autonomous identification of plutonium [8]. The complete radioisotope library is displayed in the appendix.

Finally, to differentiate our different detectors from each other, we applied Gaussian Energy Broadening (GEB), through MCNP's internal capability. GEB is determined based on the Full Width at Half Maximum (FWHM) of an energy peak, using the equation shown below.

$$\mathrm{FWHM} = a + b\sqrt{E + cE^2}$$

The values a, b, and c, which are inputs into MCNP, were determined using measured gamma spectra for all three types of detectors, CZT, Na(Tl), and HPGe, where each of their resolutions was observed at the 662 keV peak of Cs-137. The resolution is the FWHM divided by the energy of the peak. These values were determined from a comparison of gamma-ray detectors by AmpTek, a leader in the field of isotope detection. For CZT, the resolution is observed to be 1.1% FWHM, NaI(Tl) is 7% FWHM, and HPGe is 0.3% FWHM.

Our final simulated spectrum is shown below in Figure 7. Because MCNP was only able to model every energy below the 662 keV peak, we added background data taken by H3D Gamma to our simulated spectrum to make it more realistic.

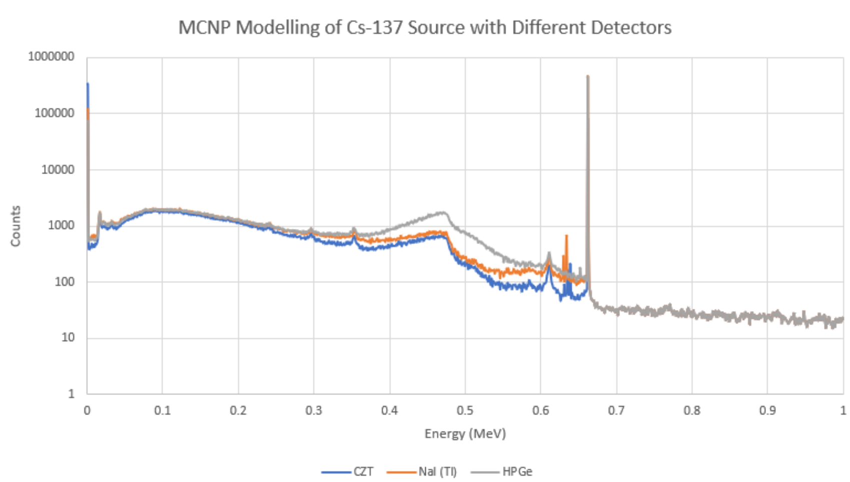


Figure. 7 Final MCNP modelling results

CHAPTER 6. RANDOM FOREST

Random Forest is a powerful machine learning algorithm that belongs to the family of ensemble methods. It is a collection of decision trees that are trained on random subsets of features and training data, which are then combined to make a final prediction. This method of combining multiple decision trees helps to overcome the limitations of individual trees, such as overfitting and high variance.

The algorithm works by randomly selecting a subset of features and training data with replacement, and then building a decision tree on this subset. This process is repeated multiple times to create a forest of decision trees, each of which is built on a different subset of features and data. During training, each tree is grown by recursively splitting the data into smaller subsets based on the selected features until a stopping criterion is met. The stopping criterion could be a maximum depth of the tree or a minimum number of samples required to make a split.
The final prediction of the Random Forest model is made by aggregating the predictions of all the individual trees. In classification tasks, the majority vote of the class predictions is taken, while in regression tasks, the mean of the predicted values is computed. This approach helps to improve the accuracy and robustness of the model, as it reduces the impact of individual trees with high variance or overfitting.

One of the key advantages of Random Forest is its ability to handle high-dimensional data with complex interactions between features. It is also resistant to overfitting, as the random sampling of features and training data helps to prevent individual trees from becoming too specialized to the training data. However, the trade-off is that the model can be computationally expensive, as it requires training multiple decision trees on different subsets of data. Additionally, tuning the hyperparameters of the model, such as the number of trees and the maximum depth of the trees, can be challenging.

In this project, Random Forest is applied to classify and predict the source of a given spectrum based on the counts in each channel number of the spectrum. The channel numbers in the spectrum are treated as features, and the algorithm is trained on a dataset that contains MCNP spectrums as well as real spectrums, where the source of each spectrum is known.

During training, the algorithm builds a forest of decision trees, where each tree is trained on a randomly selected subset of features and training data with replacement. The algorithm is trained on a dataset containing both MCNP spectrums and real spectrums, where the source of each spectrum is known, and then tested on real spectrums to predict their sources.

The model was evaluated against unknown sources and the three most probable isotopes, along with their corresponding probabilities, were identified. In this test, the model accurately detected pure Co-60 with a probability of 22.45%. This indicates that the model is capable of accurately classifying and identifying the source of a spectrum based on the counts in each channel number of the spectrum.

```
[('co60', 0.2245), ('i131', 0.2165), ('ba133', 0.197)]
```

Another test was conducted to evaluate the model's ability to detect Cs-137, and it was found to accurately identify Cs-137 with a probability of 44.3%. This further demonstrates the effectiveness of the Random Forest algorithm in accurately detecting and classifying the source of a spectrum.

```
[('cs137', 0.443), ('ra226', 0.328), ('ba133', 0.141)]
```

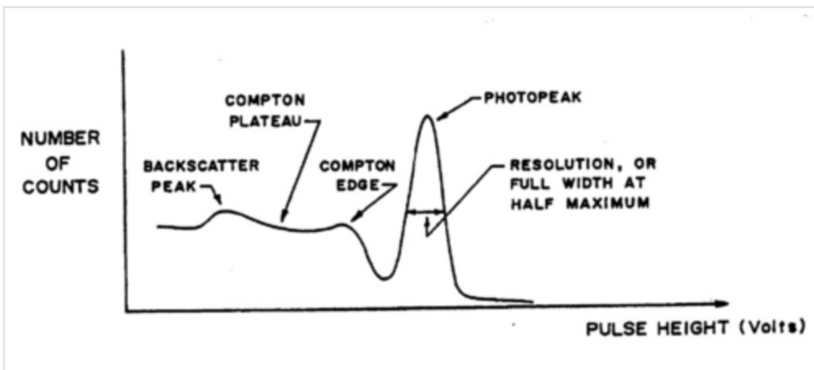
Overall, the Random Forest algorithm is a versatile and powerful machine learning technique that is widely used in various applications, including classification and regression tasks. Its ability to handle high-dimensional data and complex feature interactions, while also being resistant to overfitting, makes it a popular choice for many machine learning projects.

Moreover, Random Forest can effectively combine multiple decision trees to overcome the limitations of individual trees, resulting in more accurate and robust predictions. The model's ability to accurately identify Co-60 and Cs-137 in the tests highlights the effectiveness of Random Forest in detecting unknown sources.

In conclusion, Random Forest is a reliable and effective machine learning algorithm that can handle a wide range of tasks and is capable of achieving high accuracy in detecting and classifying unknown sources.

CHAPTER 7. PEAK IDENTIFICATION

The spectrum detected will have features and characteristics that the radionuclide isotope detector and MCNP code can recognize. The most important features are backscatter peaks. photopeaks, Compton Plateau, Compton Edge, single and double escapes. Background and electrical noise that appear in the collection of data will have to be segregated from areas of interest. A sample spectrum is shown below:



In gamma spectroscopy, identifying peaks within a spectrum is an essential step for accurate analysis. A Python code can be employed to perform peak detection in gamma spectra using a combination of the second derivative method and the Savitzky-Golay filter for count smoothing.

Second derivative method:

The second derivative method identifies peaks by detecting the points where the second derivative of the data changes from positive to negative. This change in sign corresponds to the point of inflection, which indicates the presence of a peak.

In Python, the second derivative can be calculated using the NumPy library's gradient() function, which computes the first derivative of the data. By applying the gradient() function twice, the second derivative can be obtained. Afterward, the zero-crossing points can be determined by identifying the positions where the second derivative changes from positive to negative.

Savitzky-Golay filter:

The Savitzky-Golay filter is a digital filter that fits a low-degree polynomial to a subset of data points, utilizing the method of least squares. This filter smoothens the data while preserving the essential features of the peaks, such as their positions and widths. The filter is applied by sliding a window of a specified size across the data points and fitting a polynomial (usually of low degree) to the data within the window.

In Python, the Savitzky-Golay filter can be implemented using the savgol_filter() function from the SciPy library. The function takes three primary parameters: the input data, the window size (an odd integer), and the polynomial order. The window size should be chosen carefully, as larger windows may excessively smooth the data, while smaller windows may not sufficiently reduce noise.

By combining the second derivative method and the Savitzky-Golay filter, a Python code can effectively detect peaks in gamma spectra while minimizing the impact of noise on the analysis.

The Python code presented for identifying peaks in a gamma spectrum using the second derivative method and Savitzky-Golay filter has shown promising results. However, it is important to acknowledge the limitations of the current implementation and identify potential improvements that can enhance its performance and applicability. This essay discusses the limitations and suggests future improvements for the peak identification algorithm.

- Limitations:
  - Filter Parameters:

The performance of the peak identification algorithm largely depends on the choice of Savitzky-Golay filter parameters, such as the window size and polynomial order. An inappropriate choice of parameters may lead to over-smoothing or under-smoothing the data, which can affect peak detection accuracy. The selection of these parameters often requires prior knowledge of the data or manual tuning based on trial and error.

  - Threshold Value:

The algorithm's effectiveness is also contingent on the threshold value used for peak detection. An improperly chosen threshold value may result in false positives or missed peaks. Similar to filter parameters, the threshold value may require manual tuning or optimization based on the specific data set.

  - Overlapping Peaks and Low Signal-to-Noise Ratio:

The current implementation may struggle to accurately identify overlapping peaks or peaks with low signal-to-noise ratios. Such peaks may be obscured by noise or other nearby peaks, reducing the reliability of peak identification.

- Future Improvements:
  - Robust Peak Identification Method:

To handle overlapping peaks more effectively, a more robust peak identification method could be developed. For example, implementing a deconvolution algorithm or a model-based approach, such as Gaussian mixture models, can help separate overlapping peaks and improve identification accuracy.

- Peak Fitting Techniques:

Incorporating peak fitting techniques, such as Gaussian or Lorentzian fitting, can significantly improve the estimation of peak parameters, like centroid, width, and amplitude. Peak fitting can also help address the challenge of identifying peaks with low signal-to-noise ratios by refining the initial peak estimates.

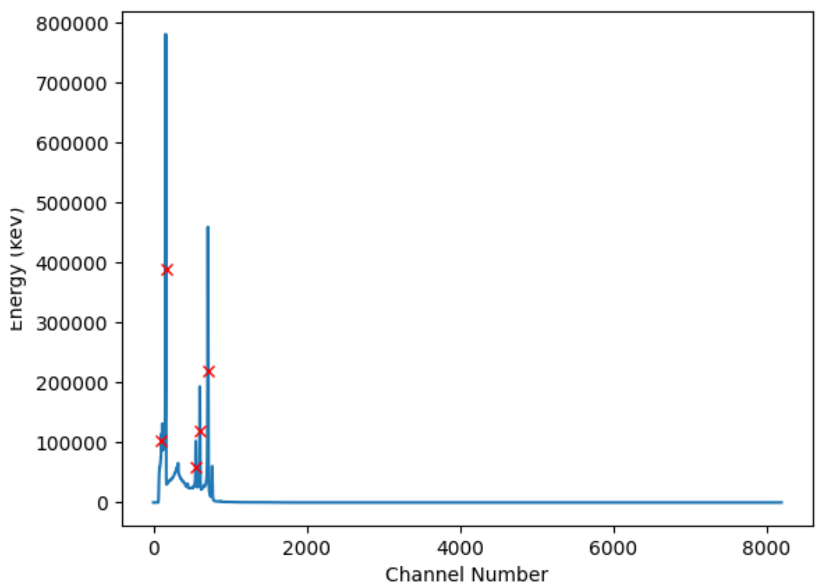
- Adaptive Filter Parameters and Threshold Values:

Developing an adaptive approach for selecting Savitzky-Golay filter parameters and threshold values can enhance the algorithm's performance across different data sets. Machine learning or optimization techniques, such as cross-validation or grid search, can be employed to automatically determine the optimal parameters for a given data set.

- User-friendly Interface and Integration:

To increase the accessibility and ease of use of the peak identification algorithm, a user-friendly graphical interface can be developed. This interface would allow users to visualize the data and interactively adjust algorithm parameters. Furthermore, integrating the code into a larger software package for gamma spectroscopy analysis would provide a more comprehensive solution for users.

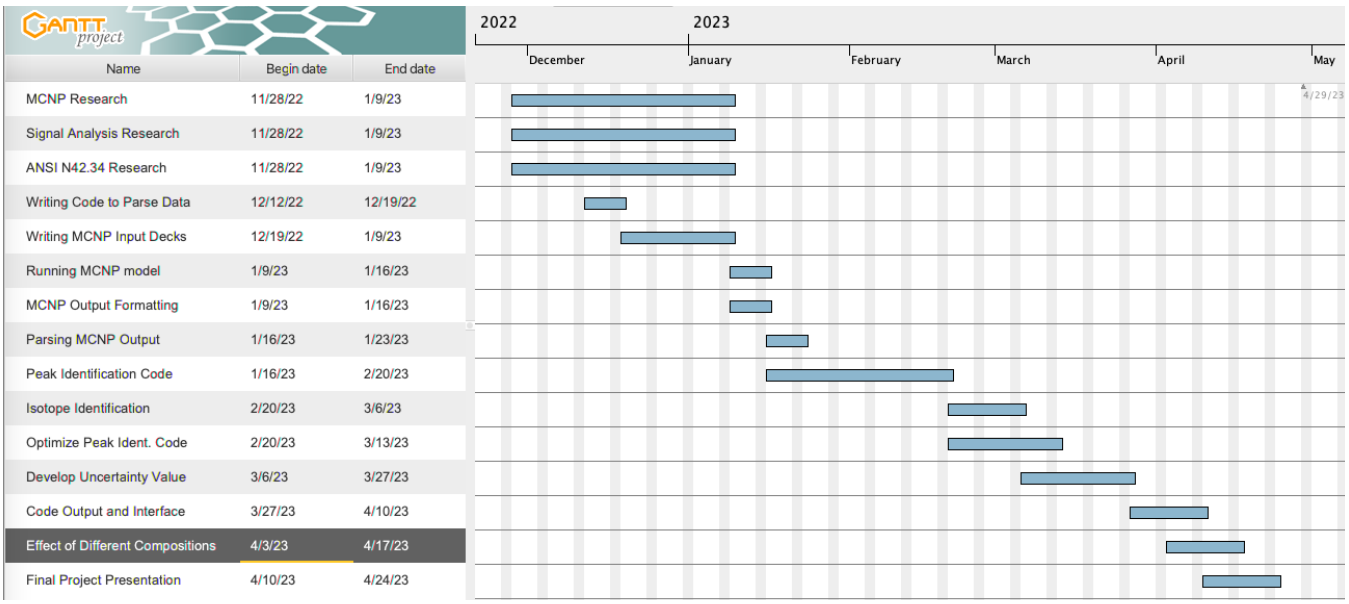
In summary, while the current implementation of the gamma spectrum peak identification algorithm using the second derivative method and Savitzky-Golay filter is effective, there are limitations that can be addressed through future improvements. By implementing a more robust peak identification method, incorporating peak fitting techniques, developing adaptive approaches for filter parameters and threshold values, and enhancing the user experience, the algorithm can become a more powerful and versatile tool for gamma spectroscopy analysis.



Ba-133 Isotope - Peak Detection

CHAPTER 8. Project Management & Organization

To ensure that activities are finished on time and in order to meet the objectives of our sponsor, the team has created a schedule for the project. This was accomplished in the form of a Gannt Chart, using the open-source Gannt Project software, version 3.1 . The figures below include the Gantt chart and a thorough analysis of its elements:



Name	Begin Date	End Date
MCNP Research	11/28/2022	01/09/2023
Signal Analysis Research	11/28/2022	01/09/2023
ANSI N42.34 Research	11/28/2022	01/09/2023
Writing code to parse data	12/12/2022	12/19/2022
Writing MCNP Input Decks	12/19/2022	01/09/2023
Running MCNP Model	01/09/2023	01/16/2023
MCNP Output Formatting	01/09/2023	01/16/2023
Parsing MCNP Output	01/16/2023	01/23/2023

Peak Identification Code	01/16/2023	02/20/2023
Isotope Identification	02/20/2023	03/06/2023
Optimize Peak Identification Code	02/20/2023	03/13/2023
Develop Uncertainty Value	03/06/2023	03/27/2023
Code Output and Interface	03/27/2023	04/10/2023
Effect of Different Compositions	04/03/2023	04/17/2023
Final Project Presentation	04/10/2023	04/24/2023

The team has created the responsibilities and strategies listed in the table below in order to best accomplish the remaining portions of the project.

Name	**Role**	**Description**
Michael Streicher	Project Manager	Main Contact from H3D
David Goodman	ANSI N42.34 Standard Committee Member	Assist with data from H3D
Abdulla Alsadid	Python / Research / Literature Reviewer	Working on Python codes for the peak identification spectrum analysis. As well as handling the research of the literature that will be part of progress for the project.
Asif Anwar	Team Communicator, Scheduler	The team member is the main point of contact with the sponsor, and will ensure project is going on track
Cullen Barber	MCNP, python code, Signals analysis, ANSI standards specialist	Will be working on the coding with both python and matlab, also responsible for research and implementation of peak identification codes. Will also focus on the

		certainty indicator for identification of radionuclides.
Jason Kot	Random Forest Developer	Work on the Random Forest Algorithm.

CHAPTER 9. CONCLUSION

As nuclear technology continues to play a critical role in our lives, the detection of radioisotopes has become increasingly essential. Recent advancements in portable gamma-ray imaging and computer vision technologies have enabled unparalleled capabilities for detecting and localizing radiological and nuclear materials in complex environments. Team H3D has developed a real-time radioisotope detection code that utilizes gamma-ray spectra generated by MCNP. Our algorithm accurately identifies radioactive sources in these spectra, and the program meets ANSI standards for radioisotope identification. This code has the potential to make a significant impact on various industries, including waste storage, defense and homeland security, healthcare, nuclear forensics, and space exploration.

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APPENDIX

Radioisotope	Composition	Photon Energy (keV)	Probability (%)
Americium-241		59.5412	35.9
Barium-133		80.997	34.06
		276.4	7.164
		302.851	18.33
		356.013	62.05
		383.848	8.94
Cobalt-57		14.4129	9.16
		122.06065	85.6
		136.47356	10.68
Cobalt-60		1173.237	99.9736
		1332.501	99.9856
Cesium-137		661.657	85.1
Gallium-67		93.311	39.2
		184.577	21.2
		300.219	16.8
Iodine-131		284.305	6.14
		364.489	81.7
		636.989	7.17
Iridium-192		295.958	28.67
		308.357	30
		316.508	82.81
		468.072	47.83
		604.415	8.23
		612.466	5.309
Potassium-40		1460.83	10.67
Technetium-99m		140.511	89.06
Thallium-201		167.43	10

Radium-226	Ra-226	186.12	3.6
	Pb-214	241.997	7.43
	"	295.224	19.3
	"	351.932	37.6
	Bi-214	609.312	46.1
	"	1120.287	15.1
Thorium-232	Pb-212	238.632	43.3
	Ac-228	338.32	11.27
	Tl-208	510.77	22.6
	"	583.191	84.5
	Ac-228	911.204	25.8
	"	968.971	15.8
Uranium-235	U-235	143.76	10.96
	"	163.33	5.08
	"	185.715	57.2
	"	205.311	5.01
	Th-231	25.64	14.5
	"	84.214	6.6
Uranium-238	Pa-234m	1001.7	0.838
	"	1737.73	0.0211
	"	1831.3	0.0172
Plutonium-239		129.296	0.00631
		375.054	0.001554
		392.53	0.000205
		413.713	0.001466
		451.481	0.0001894

Depleted Uranium (DU)	0.2% U-235	143.76	2.192
		163.33	1.016
		185.715	11.44
		205.311	1.002
		25.64	2.9
		84.214	1.32
		1001.7	0.82124
		1737.73	0.020678
		1831.3	0.016856
Highly-Enriched Uranium (HEU)	>= 90% U-235	143.76	9.864
		163.33	4.572
		185.715	51.48
		205.311	4.509
		25.64	13.05
		84.214	5.94
		1001.7	0.0838
		1737.73	0.00211
		1831.3	0.00172
Weapons-Grade Plutonium (WGPu)	<= 6.5% Pu-240 and >93% Pu-239	129.296	0.00589985
	(these values are for 6.5% 240, 93.5% 239)	375.054	0.00145299
		392.53	0.000191675
		413.713	0.00137071
		451.481	0.000177089
		45.244	0.000052
		104.234	0.0000065
		160.308	0.000000195
		642.35	0.000000065

Reactor-Grade Plutonium (RGPu)	>= 19% Pu-240, <81% Pu-239	129.296	0.0051111
	(these values are for 19% 240, 81% 239)	375.054	0.00125874
		392.53	0.00016605
		413.713	0.00118746
		451.481	0.000153414
		45.244	0.000152
		104.234	0.000019
		160.308	0.00000057
		642.35	0.00000019