A Gamma-ray Spectrum Analysis Method for Online Fuel Failure Monitoring of Nuclear Reactors

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Abstract

Abstract: In the course of nuclear reactor operation, real-time monitoring of radionuclides in the primary coolant is of great significance for timely search of fuel cladding failures and for guaranteeing safe and stable operation of the reactor. The currently prevalent off-line sampling measurement method is plagued by problems such as delayed data feedback and potential radiation exposure risks for personnel, thus making it arduous to satisfy the requirements of real-time monitoring. To address this challenge, this work proposes a novel methodology for online fuel failure monitoring via gamma-ray spectrum analysis. The core innovation lies in a synergistic algorithmic framework that uniquely integrates: a ROI-based five-point centroid smoothing algorithm for targeted noise reduction, a dynamic derivative peak-search algorithm for adaptive identification of spectral features, and a newly proposed modified Gaussian fitting algorithm for precise peak characterization. This constitutes the first integrated approach specifically designed for the dynamic and complex conditions of online monitoring. Based on the methodology, a spectrum analysis program named ORGSA (Online Real-time Gamma-ray Spectrum Analysis) is developed. The analysis results indicate that this method can realize the real-time identification and activity calculation of key nuclides such as Kr, Xe, I, and Cs in the primary coolant water. The activity error of most nuclides is within \$±\$10%, and the errors of some nuclides (e.g., 138Xe, 137Cs, 41Ar) are below 3%. The average activity measurement accuracy reaches 95%, suggesting high accuracy and robustness, providing technical support for the real-time early warning of reactor fuel element failures and safety assessment.

Full Text

Preamble

A Gamma-ray Spectrum Analysis Method for Online Fuel Failure Monitoring of Nuclear Reactors

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Abstract

Real-time monitoring of radionuclides in the primary coolant during nuclear reactor operation is crucial for timely detection of fuel cladding failures and ensuring safe, stable reactor operation. The currently prevalent offline sampling measurement method suffers from delayed data feedback and potential radiation exposure risks for personnel, making it difficult to meet real-time monitoring requirements. To address this challenge, this work proposes a novel methodology for online fuel failure monitoring via gamma-ray spectrum analysis. The core innovation lies in a synergistic algorithmic framework that uniquely integrates: a ROI-based five-point centroid smoothing algorithm for targeted noise reduction, a dynamic derivative peak-search algorithm for adaptive identification of spectral features, and a newly proposed modified Gaussian fitting algorithm for precise peak characterization. This constitutes the first integrated approach specifically designed for the dynamic and complex conditions of online monitoring. Based on this methodology, a spectrum analysis program named ORGSA (Online Real-time Gamma-ray Spectrum Analysis) is developed. The analysis results indicate that this method can achieve real-time identification and activity calculation of key nuclides such as Kr, Xe, I, and Cs in the primary coolant. The activity error of most nuclides is within \$±\$10%, with some nuclides (e.g., ^{138}Xe, ^{137}Cs, ^{41}Ar) showing errors below 3%. The average activity measurement accuracy reaches 95%, demonstrating high accuracy and robustness, and providing technical support for real-time early warning of reactor fuel element failures and safety assessment.

Keywords: Fuel failure monitoring; Gamma-ray spectrum analysis; Improved Gaussian fitting algorithm; SNIP background subtraction method

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1 Introduction

As the crucial medium for core heat extraction and radiation shielding in nuclear reactors, the radionuclide composition and activity concentration in the primary coolant directly reflect the integrity of fuel elements. Fuel elements operating over extended durations under extreme conditions—including high temperature, high pressure, intense radiation, corrosion, and vibration—may develop cladding cracks or perforations. Once the cladding is breached, fission products (such as ^{131}I, ^{137}Cs, ^{133}Xe, etc.) are released into the coolant, resulting in elevated radioactivity levels that affect both core nuclear safety and radiation safety [1-3].

Currently, nuclear power plants extensively adopt offline sampling in conjunction with gamma spectrometry utilizing HPGe (High-Purity Germanium) detectors. This approach is plagued by problems such as data lag and inadequate sample representativeness. The time span from sampling to analysis ranges from several hours to tens of hours, which fails to provide real-time feedback regarding core status. Moreover, volatile nuclides are liable to escape during the sampling process, thereby compromising the accuracy of activity measurements [4-5]. In recent years, research efforts have concentrated on developing efficient real-time radiation monitoring methods and analytical models suitable for complex environments. El-Jaby et al. [6] established a general STAR mathematical model that extends fission product release prediction to transient conditions, laying the theoretical foundation for subsequent development of fuel monitoring codes. In the area of monitoring systems and algorithms, Qin et al. (2016) [7] developed an online monitoring system based on a $LaBr_3$(Ce) detector, incorporating spectrum processing algorithms including Gaussian smoothing and morphological transformations to enable effective identification and early warning for key nuclides such as ^{135}Xe and ^{88}Kr in the primary coolant of pressurized water reactors. Similarly, Prieto et al. [8] conducted a comprehensive performance evaluation of a $LaBr_3$(Ce) water monitor, while Casasnovas et al. [9] successfully integrated a NaI(Tl) detector into an online monitoring station for waters near a nuclear power plant. Regarding data analysis and identification techniques, Barradas et al. [10] developed a method based on a one-dimensional convolutional neural network capable of automatically identifying up to 10 mixed nuclides from complex $LaBr_3$(Ce) spectra, demonstrating potential to surpass traditional software. The full-spectrum analysis technique developed by Androulakaki et al. [11] also provides an effective means for accurate resolution of multiple nuclide activities from low-resolution spectra. Prieto et al. [12] established a method for nuclide identification and quantification based on gamma spectrometry through experimental calibration and Monte Carlo simulation, validating its effectiveness in river water radioactivity monitoring using actual environmental samples.

Despite notable advancements achieved in the aforementioned research endeavors, formidable challenges persist when addressing the intricate nuclide environment within the primary circuit of a nuclear reactor. The nuclide composition in the primary circuit exhibits a high degree of complexity, where the spectra of fission products and corrosion products overlap, giving rise to pronounced Compton scattering and peak summation effects. This spectral interference substantially escalates the complexity of nuclide identification. Simultaneously, online monitoring necessitates algorithms endowed with real-time processing capabilities. Existing approaches still demonstrate room for improvement in terms of identification success rate and quantitative accuracy when applied to environments characterized by strong interference and intricate nuclide mixtures. Consequently, the development of intelligent spectrum analysis algorithms capable of adapting to complex spectral interference while maintaining both high precision and real-time performance remains a crucial technological bottleneck that urgently demands a breakthrough.

This paper presents an online analysis methodology for gamma-ray spectra. A radiation transport model of the pipeline-detector system is constructed using the MCNP (Monte Carlo N-Particle Transport Code). An optimal combination of algorithms—including five-point centroid smoothing based on ROI (Region of Interest), dynamic derivative peak search, statistical SNIP (Sensitive Non-linear Iterative Peak) background subtraction, and improved Gaussian function fitting—is integrated. Based on the proposed method, a spectrum analysis program named ORGSA (Online Real-time Gamma-ray Spectrum Analysis) is developed, offering technical support for real-time early warning of reactor fuel element failures and safety assessment.

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2 Methodology

Current methods for gamma spectrum analysis predominantly employ a processing strategy encompassing "least-squares smoothing, derivative peak searching, linear background subtraction, and Gaussian function fitting" [13-16]. These methods respectively confront problems such as peak distortion resulting from excessive smoothing, the incapability of fixed peak-searching thresholds to satisfy requirements in complex nuclide environments, insufficient handling of complex background subtraction, and the inability of standard Gaussian functions to comprehensively fit full-energy peaks. Addressing these issues, this study conducts optimization and improvement on key algorithms for gamma spectrum analysis, with specific details presented below.

2.1 The Smoothing Method

The original gamma spectrum is influenced by factors including statistical fluctuations in radiation and electronic system noise, leading to substantial counting fluctuations. Direct peak search using such spectra is prone to identifying spurious peaks or omitting authentic ones. The primary aim of smoothing preprocessing is to suppress noise while maximally preserving crucial information from characteristic peaks, such as peak position, height, and width, thus providing high-quality spectral data for subsequent peak search. To overcome the limitations of current smoothing methods, this paper proposes an adaptive ROI processing method based on count intensity.

This approach realizes comprehensive optimization from the perspectives of both smoothness and peak search performance. By dynamically adjusting smoothing parameters in accordance with count intensity in different regions of the spectrum, the method applies more intensive smoothing in high-count regions to suppress noise and milder smoothing in low-count regions to preserve peak shape characteristics, thereby enhancing the targeted efficacy of the smoothing process.

2.1.1 Current Smoothing Methods Current smoothing methods [17-19], including least-squares smoothing, five-point centroid smoothing, Gaussian smoothing, Fourier smoothing, and wavelet smoothing, achieve noise reduction through localized data processing or domain transformation. However, these five algorithms are constrained by their fixed processing paradigms and exhibit intrinsic limitations, as detailed below.

Least-squares smoothing is based on the principle of local polynomial fitting, obtaining the central value by fitting a low-order polynomial within a sliding window (typically 5-9 channels). Although it can preserve local features, the polynomial order and window width require manual pre-setting. Inappropriate parameter selection can easily lead to baseline oscillation or loss of detail. Its mathematical expression is shown in formula (1).

Five-point centroid smoothing is an intuitive smoothing method based on local weighted averaging. Its core assumption is that noise is a zero-mean random signal, and partial noise cancellation can be achieved through weighted averaging. It implements low-pass filtering via convolution. However, its weight distribution lacks flexibility, leading to insufficient suppression in high-noise regions and potential peak height attenuation in low-count regions. The mathematical expression is shown in formula (2).

Gaussian smoothing performs convolution using a Gaussian function as the weight kernel, resulting in natural smoothing and strong noise suppression capability. However, the fixed parameters of the Gaussian function make it difficult to adapt globally, potentially causing characteristic peak broadening and notably reducing the resolution of overlapping peaks. The mathematical expression for Gaussian smoothing is given by Eq. (1) to Eq. (3): where $\hat{y}_i$ is the smoothed channel count at position i and y_i represents the post-processing value and the original count represents the pre-smoothing data. Moreover, the discrete Gaussian convolution kernel g_j is denoted by Eq. (4):

The Fourier smoothing method transforms the signal into the frequency domain using the Fourier transform, attenuates high-frequency noise components, and subsequently reconstructs the signal via inverse Fourier transformation. The efficacy of this approach is contingent upon appropriate selection of the cutoff frequency. If the cutoff frequency is set excessively high, inadequate smoothing occurs; conversely, if it is set too low, over-smoothing results. Furthermore, Gibbs phenomena, characterized by ringing artifacts from the filtering process, may introduce spurious data points. The DFT (Discrete Fourier Transform) is presented in Eq. (5): $Y_k = \sum_{n=0}^{N-1} y_n e^{-i2\pi kn/N}, \quad k = 0, 1, \ldots, N-1$ where Y_k represents the k-th frequency-domain coefficient, characterizing the amplitude and phase information of the signal at frequency k, N is the length of the signal, y_n is the n-th sampling point of the discrete time-domain signal, and $e^{-i2\pi kn/N}$ is the basis function of the Discrete Fourier Transform, where i is the imaginary unit. This exponential term enables orthogonal decomposition from the time domain to the frequency domain. The frequency-domain filtering formula is given by Eq. (6): $\tilde{Y}_k = Y_k \cdot H_k$, where $H_k = 1$ for $|k| \leq k_c$ and 0 otherwise, where $\tilde{Y}_k$ is the filtered frequency-domain coefficient at index k, H_k is the filter window function in the frequency domain, and k_c is the cutoff frequency. The IDFT (Inverse Discrete Fourier Transform) is given by Eq. (7): $\tilde{y}_n = \frac{1}{N} \sum_{k=0}^{N-1} \tilde{Y}_k e^{i2\pi kn/N}$, where $\tilde{y}_n$ is the n-th sample point of the reconstructed time-domain signal after Fourier smoothing, and $1/N$ is the normalization factor of the inverse transform.

Wavelet smoothing decomposes the signal into different scales via wavelet transform and achieves noise removal by thresholding the detail coefficients. However, its threshold setting lacks adaptive adjustment capability. Coefficients with medium to low amplitudes, corresponding to weak peaks, are easily misjudged as noise and removed, leading to missed detection of genuine peaks. The wavelet decomposition is given by Eq. (8): $WC = \mathrm{DWT}(y)$, where WC denotes the set of wavelet coefficients obtained after wavelet decomposition, and DWT represents the Discrete Wavelet Transform operator. The thresholding process is given by Eq. (9): $WC_{\mathrm{soft}}(x) = \mathrm{sign}(x) \cdot \max(0, |x| - T)$, where WC_{soft} represents the wavelet coefficient after soft thresholding; $\mathrm{sign}(x)$ is the sign function, used to preserve the phase information of the wavelet coefficient; x is the original wavelet coefficient to be processed by thresholding; and T is the threshold value. Subsequently, wavelet reconstruction is performed by Eq. (10): $\hat{y} = \mathrm{IDWT}(\widehat{cA}, \widehat{cD})$, where IDWT is the Inverse Discrete Wavelet Transform operator, $\widehat{cA}$ represents the approximation coefficients after wavelet decomposition, characterizing the low-frequency contour information of the signal, and $\widehat{cD}$ represents the detail coefficients after wavelet decomposition, characterizing the high-frequency details (including noise) of the signal.

Smoothness R is an important indicator for evaluating the performance of a smoothing algorithm. It is defined as the sum of squared second-order differences of the smoothed data, given by Eq. (11): $R = \sum_{i=2}^{N-1} (y_{i-1} - 2y_i + y_{i+1})^2$, where y_i represents the smoothed spectrum count, and x_i represents the original spectrum count. A smaller R value indicates a smoother curve after processing and better noise suppression.

2.1.2 Gaussian Smoothing Algorithm Based on ROI Processing Traditional methods typically apply a uniform processing strategy across the entire spectrum, neglecting the differentiated smoothing requirements of regions with varying count intensities. This paper proposes an adaptive smoothing ROI processing method based on count intensity. This method requires initial smoothing and peak searching using traditional techniques to mark peak regions as ROI. The smoothing strength is then dynamically adjusted according to the total count within each ROI, enabling intelligent and optimized processing of the spectral data.

Let the total count within an ROI be C, the minimum count threshold be $C_{\min}$ and the maximum count threshold be $C_{\max}$. The smoothing weight w is calculated using a modified logistic function, given by Eq. (12): $w = \frac{1}{1+e^{-k(C-(C_{\min}+C_{\max})/2)}}$, where $k = 10$ is the slope parameter controlling the steepness of the transition. The corresponding smoothing strength parameter σ is determined through linear interpolation, given by Eq. (13): $\sigma = \sigma_{\min} + w(\sigma_{\max} - \sigma_{\min})$. Finally, the processed result for the ROI region is a weighted combination of the original data and the Gaussian-smoothed data, given by Eq. (14): $y_{\text{final}} = (1 - w) \cdot y + w \cdot (G_\sigma * y)$, where G_σ represents the Gaussian kernel function characterized by its standard deviation σ, and $*$ denotes the convolution operation.

The theoretical foundation of this method stems from the statistical properties of nuclear spectral data. High-count regions exhibit smaller relative statistical fluctuations and can therefore tolerate more aggressive smoothing without significant loss of valid information. Conversely, low-count regions possess greater statistical uncertainty, necessitating the preservation of more original features to avoid peak distortion caused by over-smoothing.

2.2 Peak Searching Method

Peak searching is a crucial step for identifying the characteristic peak positions (channel addresses) of target nuclides from the smoothed energy spectrum. Its accuracy directly impacts subsequent nuclide identification and activity calculation. Performance analysis of two mainstream peak search algorithms—the second derivative method and the covariance method—reveals that the traditional fixed-threshold approach performs poorly in complex nuclide environments. Consequently, a dynamic derivative method is proposed. The dynamic threshold method adjusts the threshold by estimating local noise in real-time, enabling the capture of weak peaks in low-noise regions and suppressing false peaks in high-noise regions, thereby enhancing the adaptability and accuracy of peak search.

2.2.1 Current Peak Searching Methods Current peak searching methods primarily include the derivative algorithm and the covariance peak searching algorithm [20-25].

The second derivative method processes discrete spectral data using mathematical differentiation: the second derivative of an ideal Gaussian peak corresponds to a distinct negative zero-crossing point at the peak summit. However, in the scenario of gamma spectrum peak search for primary coolant in nuclear reactors, the second derivative method employs a global fixed threshold, making it prone to missing weak peaks in low-noise regions and generating false peaks in high-noise regions. It also exhibits weak resistance to strong background interference from other nuclides and relies heavily on smoothing quality. Its second derivative calculation formula is given by Eq. (15): $d_i^{2y}/dx^2 = y_{i+1} - 2y_i + y_{i-1}$. The peak identification criteria for the second derivative method are given by Eq. (16) and Eq. (17): $d_i^{2y}/dx^2 < 0$ and $|d_i^{2y}/dx^2| >$ threshold.

The covariance peak search method is an efficient peak location identification technique based on the principle of template matching. It quantitatively evaluates shape similarity by calculating the normalized covariance coefficient between a predefined peak-shaped template and local segments of the energy spectrum data. When the template center scans to the actual peak position, this coefficient exhibits a distinct local maximum, enabling precise peak location determination. This method possesses excellent suppression capabilities against statistical fluctuation noise and complex backgrounds, making it particularly suitable for identifying overlapping peaks and weak peaks. However, it relies on a fixed peak shape template, making it difficult to adapt to actual distorted peaks. It also suffers from high computational complexity, poor real-time performance, and a tendency to miss low-activity weak peaks. The covariance calculation is given by Eq. (18): $C(i) = \frac{\sum_{k=-m}^{m}(y_{i+k}-\bar{y}_i)(T_k-\bar{T})}{\sqrt{\sum_{k=-m}^{m}(y_{i+k}-\bar{y}_i)^2 \sum_{k=-m}^{m}(T_k-\bar{T})^2}}$, where $C(i)$ is the peak criterion value at channel i, with its value range being [-1, 1]; T_k is the value of the template at the k-th offset position; m is the half-width of the template, which determines the matching range and is set based on the peak' s Full Width at Half Maximum (FWHM); and $\bar{T}$ is the average value of all elements in the template: $\bar{T} = \frac{1}{2m+1}\sum_{k=-m}^{m} T_k$.

2.2.2 The Dynamic Derivative Method The dynamic derivative method locates the positions and boundaries of overlapping peaks, weak peaks, and false peaks in the smoothed energy spectrum data. The dynamic derivative peak search algorithm enhances the inflection point characteristics of peaks by calculating higher-order derivatives of the spectrum data, thereby enabling sensitive determination of peak positions. The k-th derivative is calculated as follows: $d^k y_i/dx^k = \sum_{j=0}^{k}(-1)^j \binom{k}{j} y_{i-j}$. Unlike traditional derivative methods that often use fixed or user-defined thresholds, the dynamic threshold is not a global constant but adjusts dynamically with fluctuations in the local noise level. It estimates the noise intensity (standard deviation) in real-time within a local window around each candidate point and sets the threshold as a multiple of this noise intensity. This mechanism automatically lowers the threshold in low-noise regions to capture weak peaks and raises it in high-noise regions to suppress false positives. The dynamic threshold is calculated by Eq. (21): $T_k = \alpha \cdot \sigma_k$, where T_k is the dynamic threshold for the k-th derivative, α is the threshold factor, and σ_k is the local noise level. Its calculation is given by

Eq. (22): $\sigma_k = \sqrt{\frac{1}{2m+1}\sum_{j=-m}^{m}(y_{i+j} - \bar{y}_i)^2}$, where m is the window half-width. The dynamic threshold adapts to the noise level, resolving the inflexible threshold and template mismatch issues inherent in the previous two methods while balancing peak search accuracy and computational efficiency. It demonstrates superior performance in complex spectra.

2.2.3 Performance Evaluation Metrics for Peak Searching Algorithms

To comprehensively evaluate the performance of peak searching algorithms, four metrics are adopted: Precision, Recall, MCC (Matthews Correlation Coefficient), and F1-score. Their specific definitions are as follows.

Precision is the ratio of correctly identified true peaks to the total number of peaks identified by the algorithm, reflecting its ability to suppress false peaks. It is defined by Eq. (23): $\text{Precision} = \frac{TP}{TP+FP}$, where TP (True Positive) refers to correctly identified true peaks, and FP (False Positive) refers to non-peak regions mistakenly identified as peaks.

Recall is the ratio of correctly identified true peaks to the total number of actual true peaks, reflecting the algorithm' s ability to capture genuine peaks. It is defined by Eq. (24): $\text{Recall} = \frac{TP}{TP+FN}$, where FN (False Negative) refers to true peaks that were missed.

MCC (Matthews Correlation Coefficient) is a metric that comprehensively considers TP, TN (True Negatives), FP, and FN, measuring the balance and reliability of the algorithm' s classification. Its value ranges from [-1, 1], where a value closer to 1 indicates better performance. It is defined by Eq. (25): $\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$.

F1-Score is the harmonic mean of Precision and Recall, providing a comprehensive measure of the algorithm' s overall performance, given by Eq. (26): $\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$, where TN (True Negative) refers to correctly identified non-peak regions.

2.3 Background Subtraction Algorithms

2.3.1 Linear Background Subtraction Algorithm The linear background subtraction algorithm is a simple and intuitive approach for background handling. It operates on the fundamental assumption that the instrumental background or noise varies slowly and linearly with energy or channel number. This method is computationally highly efficient, requiring only a linear regression to fit a straight line representing the background trend, which is then subtracted from the entire spectral data. Its advantages lie in its simplicity and fast computation speed, making it suitable for ideal scenarios where the background shape is indeed approximately linear and the regions on both sides of characteristic peaks are relatively flat. However, its drawbacks are quite evident. The algorithm is an oversimplification and cannot handle the curved, sloping, or structurally complex non-linear backgrounds commonly encountered in real experiments. Forceful application can lead to under-subtraction or over-subtraction of the background on one or both sides of a peak, thereby introducing systematic errors.

2.3.2 Step Background Subtraction Algorithm The step background subtraction algorithm is a highly practical, empirical technique. It abandons the assumption of a global background shape in favor of a more reasonable local assumption: the background between characteristic peaks changes slowly and can be approximated by connecting the valley points between peaks. The core steps of this method involve accurate peak search and precise determination of peak boundaries. Its strength is its ability to handle step-like backgrounds where the background level differs significantly across various energy regions reasonably well. Its effectiveness, however, is heavily dependent on the accuracy of peak boundary identification. If the spectral signal-to-noise ratio is low, making valleys indistinct, or if overlapping peaks cause boundary ambiguity, the accuracy of the background interpolation decreases. This can subsequently lead to underestimation or overestimation of the background in the peak region.

2.3.3 The SNIP Background Algorithm The SNIP (Sensitive Nonlinear Iterative Peak) algorithm [26, 28] achieves background estimation through a simple iterative process. Its core idea is to progressively "clip" or trim the peak signals by iteratively comparing the count in each channel with the average of its neighboring channels, under the constraint of statistical fluctuations, until the result converges to the estimated background. The specific steps of the method are as follows.

LLS (Log-Log-Sqrt) transformation is applied to the counts in each channel across the entire spectrum to mitigate the effects of large disparities in count values between channels, given by Eq. (27): $z(i) = \ln(\ln(\sqrt{y(i)} + 1) + 1)$, where $z(i)$ is the transformed count and $y(i)$ is the original count.

Iterative smoothing defines the number of iterations k. For positions located in the background region, their values are typically similar to the surrounding average and will remain largely unchanged. Through multiple iterations, peaks are gradually flattened, while the background is preserved. The iterative formula is given by Eq. (28): $z_k(i) = \min\left(z_{k-1}(i), \frac{z_{k-1}(i-1)+z_{k-1}(i+1)}{2}\right)$, where z_k represents the count after the k-th iteration.

The background signal is obtained by applying the inverse LLS transform to the values after iteration. The net peak signal is then obtained by subtracting the estimated background signal from the original spectrum: $s(i) = y(i) - b(i)$, where $y(i)$ represents the original count, $b(i)$ represents the background count after inverse LLS transformation, and $s(i)$ represents the net peak count.

The SNIP method does not require preset background models and can adaptively fit complex-shaped backgrounds. It is particularly suitable for complex spectra with continuous backgrounds and overlapping peaks, making it widely used in gamma spectrum analysis.

2.4 Full-Energy Peak Fitting Methods

In gamma spectrum analysis, function fitting is a key mathematical technique for extracting physical parameters from experimental measurement data. The core task involves establishing an appropriate mathematical model to approximate the measured spectral line, which is affected by statistical fluctuations, noise, and background interference, thereby precisely determining parameters such as the position, area, and full width at half maximum (FWHM) of characteristic peaks. This provides a reliable basis for the qualitative and quantitative analysis of nuclides. Currently, full-energy peak fitting primarily relies on two methods: the Gaussian function and Fourier series [29-31]. However, traditional methods have limitations. Thus, this paper proposes an improved adaptive Gaussian peak fitting algorithm and an improved Fourier series fitting algorithm, as detailed below.

2.4.1 Current Full-Energy Peak Fitting Methods Gaussian function fitting is one of the classical methods for peak analysis, based on the fundamental assumption that the shape of an ideal characteristic peak closely approximates a symmetric Gaussian distribution. By fitting a Gaussian function curve to a specific peak region in the spectral data, key physical parameters of the peak —namely, the peak position (channel), peak area, and peak width (FWHM)— are extracted. The mathematical formula for the standard Gaussian function is given by Eq. (30): $G(x) = A\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$, where $G(x)$ is the value of the Gaussian function at x, representing the fitted count; A is the amplitude determining the height of the peak; μ is the mean value determining the center position of the peak, corresponding to the peak channel; and σ is the standard deviation determining the width of the peak.

Area is the integrated area, representing the total count of the characteristic peak, which is proportional to the content of the radionuclide. It is calculated by Eq. (31): $\text{Area} = A\sigma\sqrt{2\pi}$.

The FWHM (Full Width at Half Maximum) is the width of the peak at half its maximum height. It is a key indicator for measuring the energy resolution of a detector. The calculation formula is given by Eq. (32): $\text{FWHM} = 2\sqrt{2\ln 2}\,\sigma$.

Fourier series fitting method treats an isolated peak shape as a complex waveform, approximating it through a linear combination of sine and cosine functions with different frequencies, amplitudes, and phases. Since the Fourier series fundamentally describes periodic functions, it is more suitable for fitting isolated, enclosed, and approximately symmetric peak structures. Its advantage lies in its ability to flexibly capture subtle deviations in the peak shape, such as slight asymmetry or specific shoulder structures, by including higher-order terms—features that the standard Gaussian function may struggle to represent accurately. For an isolated peak defined within the interval $[0, L]$, its shape is approximated using a truncated Fourier series, given by Eq. (33): $P(x) = \frac{a_0}{2} + \sum_{n=1}^{N} \left[a_n \cos\left(\frac{2\pi nx}{L}\right) + b_n \sin\left(\frac{2\pi nx}{L}\right)\right]$, where $P(x)$ is the fitted peak shape function; a_0, a_n, and b_n are the Fourier coefficients; n is the order of the Fourier series; and L is the total width of the interval containing the peak.

The peak area requires approximate calculation through numerical integration of the fitted function $P(x)$ over the peak interval: $\text{Area} = \int_{x_{\text{start}}}^{x_{\text{end}}} P(x)dx$, where x_{start} and x_{end} define the lower and upper limits of the peak region, respectively.

Consequently, the complete spectral model is a superposition of multiple peaks (represented by Fourier series or a combination with other functions) and a background function: $\text{Spectrum}(x) = B(x) + \sum_{i=1}^{M} f_i(x)$, where $\text{Spectrum}(x)$ represents the total spectral count, $B(x)$ is the background function, $f_i(x)$ is the fitting function for the i-th peak, and M is the number of peaks in the energy spectrum.

2.4.2 The Improved Gaussian Function Fitting Algorithm To address the inability of the traditional Gaussian function to handle asymmetric peaks, this paper proposes an improved adaptive Gaussian peak fitting algorithm. By integrating an asymmetric Gaussian function with an exponential tail component, it effectively overcomes the limitations of traditional Gaussian fitting when dealing with asymmetric peak shapes, thereby enhancing fitting accuracy and reliability and providing an effective tool for high-precision quantitative spectrum analysis. This function consists of a standard Gaussian component and an exponential tail component, given by Eq. (36): $f_{\text{peak}}(x) = f_{\text{Gaussian}}(x) + f_{\text{tail}}(x)$, where $f_{\text{peak}}(x)$ is the improved Gaussian fitting function, and the expression for its asymmetric modifier tail $f_{\text{tail}}(x)$ is given by Eq. (37): $f_{\text{tail}}(x) = \frac{A_{\text{tail}}}{2} \exp\left(\frac{x-\mu}{\lambda}\right) \text{erfc}\left(\frac{x-\mu}{\sqrt{2}\sigma} + \frac{\sigma}{\sqrt{2}\lambda}\right)$, where A_{tail} is the amplitude of the tail, λ is the tail decay constant, and erfc is the complementary error function, ensuring a smooth and physically reasonable connection between the main Gaussian body and the exponential tail. The complementary error function (erfc) is defined by Eq. (38): $\text{erfc}(z) = \frac{2}{\sqrt{\pi}} \int_{z}^{\infty} e^{-t^2} dt$.

The complete fitting model is the superposition of the peak function and the background function, given by Eq. (39): $y(x) = f_{\text{peak}}(x) + B(x)$. The peak area after background subtraction is calculated by numerical integration, given by Eq. (40): $\text{Area} = \int_{x_{\text{start}}}^{x_{\text{end}}} [y(x) - B(x)]dx$.

2.4.3 The Improved Fourier Series Fitting Algorithm Traditional Fourier series are prone to overfitting due to high-frequency noise interference when higher-order terms are included. This study introduces a weighted modification of the Fourier coefficients using a Hanning window function, which preserves peak shape details while suppressing high-frequency noise, thereby ensuring fitting stability. This method is particularly suitable for fitting peaks with irregular shapes, asymmetry, or complex fine structures, serving as a valuable supplement to traditional Gaussian fitting.

To suppress noise introduced by higher-order harmonics, the Hanning window function is applied to weight the Fourier coefficients, reducing the risk of overfitting by smoothing the high-frequency components. The Hanning window function is given by Eq. (41): $w_i = 0.5\left[1-\cos\left(\frac{2\pi i}{N-1}\right)\right], \quad i = 0, 1, \ldots, N-1$, where w_i is the weighting coefficient of the i-th window function, and N is the total order of the Fourier series.

Based on the innovative methods proposed above for smoothing, peak search, background subtraction, and full-energy peak fitting, this paper has developed the integrated ORGSA (Online Real-time Gamma-ray Spectrum Analysis) spectrum analysis program. The core advantage of this program lies in the holistic optimization of the processing workflow and its adaptive capabilities.

Firstly, the adaptive ROI smoothing algorithm based on count intensity provides high-fidelity, low-noise spectral data for subsequent analysis. Subsequently, the dynamic derivative peak search method effectively enhances the identification accuracy and reliability for weak and overlapping peaks in complex nuclide environments. Then, the SNIP algorithm is utilized for precise background modeling and subtraction, overcoming the limitations of traditional linear background methods in handling complex continuous backgrounds. Finally, refined fitting of full-energy peaks is achieved using the improved asymmetric Gaussian function, significantly enhancing the accuracy of peak area quantification. Through the synergistic operation of the aforementioned algorithms, the ORGSA program systematically addresses key issues present in existing methods, such as peak distortion, missed/false peak search, background subtraction deviations, and imperfect fitting, providing a comprehensive, accurate, and robust solution for gamma spectrum analysis in complex scenarios.

Furthermore, ORGSA is equipped with an interactive visualization interface that transforms advanced algorithms into an intuitive and controllable operational experience through multi-view coordination, real-time parameter adjustment, and graphical result display. Consequently, it offers users an integrated, high-precision, and robust complete solution spanning from data preprocessing and accurate peak search to background subtraction and peak area quantification.

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3 Results and Discussion

3.1 Online Measurement of Gamma-Ray Spectrum Performed with Monte Carlo Simulation

In the source term analysis of the reactor primary circuit, key nuclides such as krypton, xenon, iodine, and cesium are selected as diagnostic indicators, primarily based on their characteristic behaviors in fuel failure and burnup assessment.

The total specific activity of noble gases serves as a general indicator for judging the integrity of the fuel cladding. Iodine equivalent activity, calculated by converting the activities of various iodine isotopes into an equivalent ^{131}I activity based on radiological dose effects, comprehensively reflects the contribution of iodine to the total dose.

The specific activity of ^{133}Xe is commonly used to directly determine whether a fuel element has failed. A specific nuclear power plant sets a threshold of 900 Bq/mL, and different reactor types can define their own limits accordingly. Nuclide ratios provide deeper diagnostic information. The ^{133}Xe/^{135}Xe and ^{131}I/^{133}I ratios both decrease with increasing breach size and are often used to assess the extent of the breach. The ^{134}Cs/^{137}Cs ratio is used for burnup analysis. Since ^{134}Cs is produced by neutron capture of ^{133}Cs, its accumulation is related to the square of the burnup, while the activity of ^{137}Cs is approximately linear with burnup. Combined with the relatively short half-life of ^{134}Cs (2.062 years), this ratio can indirectly indicate the burnup depth of the fuel assembly.

This study selected two types of gamma spectra—chemical sampling and online measurement—to validate the spectrum analysis method, with the key distinction lying in the background complexity of the spectra. As shown in the comparison between Table 1 and Table 2 , the chemical sampling spectra exhibit clear target nuclides with low interference levels. In contrast, the online measurement spectra contain various high-intensity interfering nuclides such as ^{41}Ar, ^{58}Co, and ^{51}Cr, resulting in complex spectral lines. This makes the online spectra more suitable for testing the method' s activity calculation accuracy and anti-interference capability under complex background conditions.

Table 1. Activities of radioactive nuclides obtained by chemical sampling

Chemical sampling nuclides	Specific activity (Bq/mL)
^{85}mKr	3.98E+05
^{133}Xe	6.61E+04
^{135}Xe	1.17E+05
^{138}Xe	8.52E+05
^{131}I	2.07E+06
^{132}I	1.34E+05
^{137}Cs	6.72E+04
^{134}Cs	3.90E+05
^{88}Kr	6.30E+04
^{41}Ar	6.20E+05
^{124}Sb	1.53E+06
^{58}Co	1.09E+06

Table 2. Activities of radioactive nuclides obtained by online measurement

Online measurement nuclides	Specific activity (Bq/mL)	Online measurement nuclides	Specific activity (Bq/mL)	Online measurement nuclides	Specific activity (Bq/mL)
^{85}mKr	1.67E+05	^{133}Xe	5.33E+04	^{137}Cs	4.30E+04
^{135}Xe	1.67E+05	^{41}Ar	1.41E+06	^{134}Cs	2.95E+04
^{138}Xe	4.68E+04	^{51}Cr	4.56E+05	^{124}Sb	3.63E+05
^{131}I	4.56E+05	^{58}Co	4.30E+04	^{88}Kr	1.28E+05
^{132}I	4.38E+05	^{60}Co	1.90E+06		

The Monte Carlo code MCNP is employed for simulation of gamma-ray spectra of the primary coolant. The schematic diagram of the detector model is shown in Fig. 1 [Figure 1: see original paper]. Cell 1 represents the position of all detector components except the crystal. Cell 7 is the high-purity germanium crystal. Cell 2 is the front end cap. Cell 3 is the lead shielding. Cell 4 is the tungsten shielding. Cell 6 is the stainless steel isolation layer, and Cell 8 is the pipeline model. The model is validated by comparing calculation results with the known activities of calibration sources ^{133}Ba, ^{137}Cs, and ^{60}Co, achieving an accuracy better than $±$3% within the energy range of 0.1 MeV to 1.7 MeV.

Fig. 1. MCNP model of the detector and pipeline

Gaussian broadening of the high-purity germanium spectrometer' s energy response is fitted using experimental data [28]. The fitting result is given by Eq. (42): $\mathrm{FWHM}(E) = 0.00102828 + 0.00148606\sqrt{E}$ (with E in MeV).

Based on the above modeling, gamma-ray transport simulation is performed using MCNP, and the resulting simulated energy spectrum of the high-purity germanium spectrometer is shown in Fig. 2 [Figure 2: see original paper].

Fig. 2. Simulated gamma-ray spectra of chemical sampling and online measurement

As shown in Fig. 2, the chemical sampling spectrum exhibits relatively fewer peaks and a cleaner spectral shape, with prominent characteristic peaks (such as the strong peak at 0.2 MeV) and minimal interfering peaks. This indicates that the offline separation process in chemical sampling effectively reduces nuclide complexity, allowing the spectrum to present the energy characteristics of target nuclides more clearly. In contrast, the online measurement spectrum displays more complex peaks, with numerous dense peak signals in the low-energy region ($<$ 1.0 MeV). This reflects the influence of multiple interfering nuclides from real-time nuclear reactions in the online measurement scenario, resulting in a more complex nuclide composition and greater interference factors, which poses greater challenges to the spectrum analysis capability of the unfolding program.

3.2 ORGSA Program Analysis

3.2.1 ORGSA Program Interface and Spectra Analysis Process The ORGSA program integrates algorithms such as adaptive smoothing, dynamic derivative peak search, SNIP background subtraction, and asymmetric Gaussian fitting. It encompasses functions including spectrum reading, data preprocessing, accurate peak search, background subtraction, and quantitative peak area analysis. The program' s visualization interface and spectrum analysis process are illustrated in Fig. 3 [Figure 3: see original paper].

Fig. 3. ORGSA program interface and spectrum analysis process

(a) Program operation and visualization interface

(b) Spectrum analysis process

3.2.2 Gamma-Ray Spectra Analysis of Chemical Sampling and Online Monitoring Measurements To verify the spectrum analysis accuracy of traditional chemical sampling spectra, the ORGSA program is applied to analyze the chemical sampling spectrum introduced in Sec. 3.1, with the results shown in Fig. 4 [Figure 4: see original paper].

Fig. 4. The analyzed results of chemical sampling spectrum

Statistical analysis of the measured nuclide activities in Fig. 4 reveals certain deviations between the calculated activities and the preset values, with error margins ranging from -1.63% to 25.46%. Among these, ^{138}Xe (1768.00 keV) and ^{88}Kr (2195.00 keV) demonstrated the smallest measurement errors (both below 0.35%), indicating high measurement accuracy. In contrast, significant errors exceeding 20% are observed for ^{131}I, ^{138}Xe (423.00 keV), and ^{132}I, suggesting potential systematic deviations in search efficiency calibration or interference correction within the corresponding energy ranges. Overall, the activity calculation errors for most nuclides were controlled within 20%, demonstrating the fundamental reliability of the adopted measurement and calculation methodology. However, further optimization of spectrum analysis and efficiency calibration remains necessary for specific nuclides in the medium-to-low energy range.

To visually compare the differences between the nuclide activity results calculated by the ROI method and the preset activities, the ORGSA program is used to process the online spectrum with both non-ROI and ROI-based spectrum analysis methods. The results are shown in Fig. 5 [Figure 5: see original paper] and Fig. 6 [Figure 6: see original paper], respectively.

Fig. 5. The analyzed results of online measurement spectrum

Figure 5 displays the comparison between the preset activities of various nuclides in the online spectrum and the activities calculated without the ROI method, and the comparison between the ROI-calculated activities and the preset activities.

Fig. 6. Relative errors of ROI and ROI-free calculation

As shown in Fig. 6, the measurement errors for most nuclides are controlled within $±$20%, indicating good overall reliability and accuracy of the measurement system with an average precision of approximately 82.5%. However, significant errors persist in the calculated results for certain individual nuclides. The calculation results using the ROI method are presented in Fig. 6, where the left chart compares the preset activities with the ROI-calculated activities for each nuclide, and the right chart displays the corresponding measurement errors. The results demonstrate that the ROI method generally yields smaller measurement errors compared to the non-ROI method, with most nuclide errors controlled within $±$10% and an average precision reaching as high as 95%, further validating the advantage of the ROI method in complex spectrum analysis.

3.2.3 Analysis of Online Monitoring Noisy Spectrum To validate the performance of the ORGSA program in suppressing statistical fluctuation noise, a gamma spectrum with a signal-to-noise ratio of 3:1 is analyzed, as shown in Fig. 7 [Figure 7: see original paper].

Fig. 7. Calculation results of the noisy spectrum processed by the ORGSA program

As shown in Fig. 7, the left-hand panel illustrates the comparison between the preset activities of various nuclides and the activities calculated from the noisy spectrum, while the right-hand panel shows the corresponding measurement errors. To quantitatively evaluate the accuracy of different activity calculation methods under complex spectral conditions, 14 representative nuclides are selected for analysis, such as ^{85}mKr, ^{135}Xe, and ^{131}I. A systematic comparison is carried out between the calculated activities and their relative errors obtained by the non-ROI method, the noisy spectrum calculation method, and the ROI method under preset activity conditions. The comparative results are presented in Table 3 .

Table 3. Analyzed results of the simulated spectrum

Nuclide	Energy (keV)	Preset activity (Bq/mL)	Non-ROI activity (Bq/mL)	Noisy spectrum activity (Bq/mL)	ROI activity (Bq/mL)	Non-ROI error	Noisy spectrum error	ROI error
^{85}mKr	151.18	1.67E+05	3.98E+05	1.54E+05	1.67E+05	138.37%	-7.86%	0.18%
^{135}Xe	249.79	5.33E+04	4.64E+04	4.29E+04	4.74E+04	-13.04%	-19.51%	-11.17%
^{138}Xe	258.29	4.68E+04	4.44E+04	4.87E+04	4.52E+04	-4.97%	4.18%	-3.24%
^{131}I	364.48	4.56E+05	3.48E+05	4.84E+05	4.59E+05	-23.76%	6.10%	0.62%

Nuclide	Energy (keV)	Preset activity (Bq/mL)	Non-ROI activity (Bq/mL)	Noisy spectrum activity (Bq/mL)	ROI activity (Bq/mL)	Non-ROI error	Noisy spectrum error	ROI error
^{132}I	522.66	4.30E+04	4.35E+04	1.39E+04	4.23E+04	1.20%	-67.70%	-1.71%
^{137}Cs	661.66	3.63E+05	3.53E+05	3.84E+05	3.45E+05	-2.50%	5.83%	-4.73%
^{41}Ar	1293.64	2.32E+04	2.51E+04	2.93E+04	2.26E+04	8.95%	26.39%	-2.62%
^{88}Kr	2195.84	5.02E+04	5.14E+04	1.28E+05	5.34E+04	2.42%	155.18%	6.39%
^{124}Sb	1691.02	2.80E+05	2.73E+05	3.10E+05	3.03E+05	-2.29%	10.71%	8.31%
^{60}Co	1332.50	4.34E+05	4.15E+05	5.04E+05	4.94E+05	-4.39%	16.23%	13.92%
^{58}Co	810.76	1.90E+06	2.31E+06	2.03E+06	2.02E+06	22.02%	7.06%	6.56%
^{51}Cr	320.08	4.38E+05	4.29E+05	4.49E+05	4.43E+05	-2.09%	2.46%	1.21%

As illustrated in Table 3, among the three activity calculation methods, the ROI method demonstrates superior and stable computational accuracy, with errors controlled within 10% in the vast majority of cases. This performance is significantly better than the non-ROI method, which shows instability and may produce extreme errors (e.g., 138.37% for ^{85}mKr), and the noisy spectrum calculation method, which is susceptible to specific interference (e.g., -67.70% for ^{132}I). Therefore, the ROI method is confirmed as the most reliable approach for precise activity quantification in this study.

3.3 Analysis of Algorithm Performance and Program Robustness

3.3.1 Performances of the Spectrum Smoothing Algorithms To systematically evaluate and identify the optimal smoothing algorithm, performance metrics of various smoothing algorithms were assessed. A comparison of the core performance indicators is presented in Table 4 and Table 5 , which systematically display the specific numerical values of each algorithm in terms of smoothing degree and peak search performance, providing direct data support for subsequent analysis. Correspondingly, Fig. 8 [Figure 8: see original paper] visually illustrates the morphological differences in the energy spectrum curves and the peak identification effects after processing by different algorithms.

Table 4. Smoothing degree of five smoothing algorithms

Smoothing method	Smoothing degree R
Least squares	0.0846

Smoothing method	Smoothing degree R
Five-point centroid	0.0748
Fourier method	0.0923
Gaussian smoothing	0.0646
Wavelet method	0.0812

Table 5. Impact of different smoothing algorithms on peak search

Smoothing method	Recall	Precision	F1/Acc
Least squares	86.36%	76.00%	80.85%
Five-point centroid	95.45%	84.00%	89.36%
Fourier method	81.82%	72.00%	76.60%
Gaussian smoothing	90.91%	80.00%	85.11%
Wavelet method	77.27%	68.00%	72.34%

Fig. 8. Impact of different smoothing algorithms on peak search

The comprehensive evaluation of the five spectral smoothing algorithms demonstrates that the five-point centroid method achieves the optimal balance between peak search performance and smoothing degree. It leads comprehensively across all four peak search metrics while maintaining excellent smoothing performance ($R = 0.0748$), establishing it as the smoothing method with the best overall performance. Gaussian smoothing exhibits the strongest denoising capability ($R = 0.0646$) and can serve as an effective alternative in high-noise scenarios. The remaining methods either suffer from insufficient smoothing leading to significantly reduced peak search reliability, or demonstrate mediocre performance, with overall effectiveness far inferior to the two aforementioned methods. Therefore, the five-point centroid method is confirmed as the most valuable preprocessing algorithm for application in this study.

3.3.2 Performances of the Peak Search Algorithms To evaluate the performance of different peak search algorithms, a comparative analysis of the second derivative method, the high-order dynamic derivative method, and the covariance peak search method is conducted on the same dataset, with key metrics presented in Table 6 .

Table 6. Performance comparison of different peak search algorithms

Performance metric	Second derivative method	Dynamic derivative method	Covariance method
Recall	86.36%	95.45%	72.73%
Precision	76.00%	95.45%	80.00%
F1/Acc	80.85%	95.45%	76.19%

Performance metric	Second derivative method	Dynamic derivative method	Covariance method
MCC	62.34%	90.91%	52.73%

Fig. 9. Performance comparison of different peak search algorithms for noisy spectra

Based on the comprehensive evaluation of four key metrics, the dynamic derivative algorithm demonstrates the best overall performance, achieving 95.45% in Recall, Precision, and F1-score, with an MCC of 90.91%. This indicates that the dynamic derivative algorithm possesses high accuracy and robustness in classifying positive and negative samples, essentially achieving unbiased optimal classification performance. In contrast, both the second derivative algorithm and the covariance algorithm exhibit shortcomings to varying degrees, with all metrics, particularly MCC and F1-score, significantly lower than those of the dynamic derivative algorithm. Therefore, the dynamic derivative algorithm is confirmed as the peak search algorithm with the best comprehensive performance and highest stability.

3.3.3 Performances of the Background Subtraction Algorithms To address the limitations of the traditional linear background subtraction method when dealing with complex continuous backgrounds, the adaptability of multiple advanced algorithms are compared and analyzed, including SNIP and step subtraction, and systematically evaluated their capability to suppress background subtraction deviations. The results are shown in Fig. 10 [Figure 10: see original paper].

Fig. 10. Spectrum analysis results using different background subtraction methods

The results clearly demonstrate that different background subtraction algorithms significantly impact the accuracy of spectrum analysis. The SNIP background subtraction algorithm, leveraging its nonlinear iterative characteristics, more precisely conforms to complex background shapes, effectively avoiding issues of under-subtraction or over-subtraction. It exhibits optimal performance in controlling analysis errors across most energy regions. The step background subtraction method shows certain advantages in energy regions where the background exhibits step-like changes; however, its errors increase in areas with significant background fluctuations due to limitations in accurately identifying peaks and valleys. The linear background subtraction method, based on the assumption of a linearly varying background, shows significant errors in regions with complex background shapes and is only suitable for idealized scenarios with simple backgrounds.

3.3.4 Performances of the Full-Energy Peak Fitting Algorithms The activity calculation accuracy of full-energy peak fitting using different functions is investigated in this section, including the improved Gaussian function, improved Fourier series, standard Gaussian function, and standard Fourier series, as shown in Fig. 11 [Figure 11: see original paper].

Fig. 11. Performances of full-energy peak fitting algorithms

Compared to the other algorithms, both the improved Gaussian function and the improved Fourier series exhibit outstanding accuracies in activity calculation. The majority of percentage errors remain within $±$10%, and the calculated activities show high consistency with the preset values. In contrast, these two improved methods demonstrate significant advantages in spectrum analysis precision, indicating superior reliability.

3.4 Robustness Analysis of the ORGSA Program

To validate the effectiveness and adaptability of the online spectrum analysis algorithm, a benchmark dataset comprising 15 groups of spectra with randomized characteristics is generated using numerical simulation methods. By simulating the online spectrum analysis process, full-spectrum analysis is performed on each spectrum to obtain quantitative results for the corresponding nuclide types and their activity concentrations. The results indicate that the spectrum analysis method proposed in this paper maintains stable analysis accuracy when confronted with different statistical fluctuations and spectral morphological variations, with the analysis results exhibiting strong consistency with the preset ground truth. This systematic testing confirms that the described spectrum analysis process possesses reliable analytical capabilities and engineering application potential in complex spectral environments, providing data support and a methodological basis for the subsequent optimization of online spectrum analysis systems.

Fig. 12. The analyzed results of gamma-ray spectra of continuous online measurement

As shown in Fig. 12 [Figure 12: see original paper], the calculated activity concentrations for the vast majority of nuclides are closely aligned with their preset ground truth values. The overall error distribution indicates that the absolute relative deviations for most data points are concentrated within 10%. Key nuclides such as ^{58}Co and ^{137}Cs, in particular, demonstrate stable calculation accuracies and high reproducibility across multiple measurements. Although certain nuclides exhibit slightly larger relative deviations, these cases primarily occur with nuclides characterized by low activity concentrations or significant spectral overlap in specific spectra. This observation aligns with the general principles of gamma spectrum analysis and can be mitigated through further optimization of peak area algorithms and overlapping peak resolution strategies.

In summary, the developed spectrum analysis methodology successfully achieves rapid and accurate online analysis of multi-nuclide spectra. The high consistency between calculated results and expected values verifies its effectiveness and reliability for real-time monitoring and nuclide identification applications.

4 Conclusion

A gamma spectrum analysis method is proposed to address the real-time monitoring of fuel failure in nuclear reactor primary coolant, which integrates an ROI-based five-point centroid smoothing algorithm, a dynamic derivative peak search algorithm, and an improved Gaussian function fitting algorithm. Based on this methodology, the gamma-ray spectra analysis program ORGSA is developed. The activity errors of most nuclides are within $±$10%, with some nuclides (e.g., ^{138}Xe, ^{137}Cs, ^{41}Ar) showing errors below 3%. The average activity measurement accuracy reaches 95%, suggesting high accuracy and robustness of the proposed method, which provides technical support for real-time early warning of reactor fuel element failures and safety assessment and enables rapid identification of key nuclides and accurate calculation of their specific activities. Compared to existing methods, the proposed approach demonstrates significant advantages in accuracy, real-time performance, and robustness, providing effective technical support for the safe operation of nuclear reactors.

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