A Study on the Long-Term Variation of Signal Current in Rhodium Self-Powered Neutron Detectors Under In-Core Burnup Conditions

Authors: Guo, Dr. Zhiqi, Dr. Wenhua Yang, Dr. Jingyi Han, Zhang, Prof. Shuo, Li, Dr. Zhan, Zhang, Dr. Chunhui, Prof. Dingjun Zhu, Shao, Prof. Jianxiong, Professor Jianxiong Shao

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Abstract

As a key instrument for measuring neutron flux within a reactor core, the signal current of a Self-Powered Neutron Detector (SPND) is subject to change due to continuous material burnup.Accurately accounting for the long-term evolution of SPND signals is essential for reliable power monitoring and safe reactor operation. This study focuses on the Rhodium Self-Powered Neutron Detector (Rh-SPND) and, within the context of a typical Pressurized Water Reactor (PWR), develops a predictive model for signal current variation using a Back Propagation Neural Network (BPNN). The model incorporates changes in emitter material composition due to burnup and utilizes a layered approach to calculate the radial distribution of burnup. Key parameters such as beta electron generation rate, escape probability, gamma photon generation, and gamma-induced electron escape rate are all taken into account. Results show that over a 10-year period at a neutron flux of 1\$×10^{14}\$ n/(cm^2 • s), the smaller the radius of the rhodium wire, the greater the variation in detector sensitivity. Specifically, a 0.1 mm wire radius results in a 51.3% sensitivity reduction, while a 1 mm wire radius yields a 25.2% reduction. The proposed model enables accurate sensitivity compensation for Rh-SPNDs over time, thereby minimizing neutron flux measurement errors and enhancing reactor safety and stability.

Full Text

Preamble

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Zhiqi Guo[1,2,3], Wenhua Yang[3], Shuo Zhang[1,2], Zhan Li[1,2], Jingyi Han[1,2], Chunhui Zhang[1,2], Dingjun Zhu[1,2], Jianxiong Shao[1,2*]

[1]School of Nuclear Science and Technology, Lanzhou University, Gansu, PR China
[2]Gansu Key Laboratory of Advanced Nuclear Energy and Equipment Technology, Lanzhou University, Gansu, PR China
[3]Nuclear Power Institute of China, Chengdu, Sichuan, China

Abstract: As a key instrument for measuring neutron flux within a reactor core, the signal current of a Self-Powered Neutron Detector (SPND) evolves continuously due to material burnup during operation. Accurately accounting for the long-term evolution of SPND signals is essential for reliable power monitoring and safe reactor operation. This study focuses on the Rhodium Self-Powered Neutron Detector (Rh-SPND) and develops a predictive model for signal current variation using a Back Propagation Neural Network (BPNN) within the context of a typical Pressurized Water Reactor (PWR). The model incorporates changes in emitter material composition due to burnup and utilizes a layered approach to calculate the radial distribution of burnup. Key parameters such as beta electron generation rate, escape probability, gamma photon production, and gamma-induced electron escape rate are all taken into account. Results show that over a 10-year period at a neutron flux of 1×10^{14} n/(cm$^2\cdot$s), the smaller the radius of the rhodium wire, the greater the variation in detector sensitivity. Specifically, a 0.1 mm wire radius results in a 51.3% sensitivity reduction, while a 1 mm wire radius yields a 25.2% reduction. The proposed model enables accurate sensitivity compensation for Rh-SPNDs over time, thereby minimizing neutron flux measurement errors and enhancing reactor safety and stability.

Keywords: Rh-SPND; Burnup; Long-Term Signal Current Evolution; BPNN; Prediction Model

1 Introduction

During reactor operation, the neutron flux in the reactor core is closely related to the safe and stable operation of the reactor as well as the mapping of reactor power density [?]. Therefore, real-time monitoring of neutron flux in the reactor core is particularly important [?]. As one of the tools for online monitoring of in-core neutron flux, the Self-Powered Neutron Detector has been widely used in both research and commercial reactors [?]. Compared with traditional fission chambers and activation neutron detectors, SPNDs have the advantages of requiring no external power supply, simple structure, small size, and easy installation [?]. In the process of in-core use, the emitter of the SPND continuously undergoes reactions with neutrons, resulting in material consumption. Consequently, the signal current gradually deviates over time [?]. In order to achieve real-time and accurate monitoring of the reactor core' s neutron flux, it is crucial to properly account for SPND burnup [?]. Yaodong Sang et al. conducted a study on the burnup of Ag-SPND and found that after 10.5 years of operation, the neutron sensitivity decreased by 16.68%, while the sensitivity to external gamma rays remained nearly unchanged throughout the entire period [?].

A. A. Khrutchinsky studied the burnup of Rh-SPND emitters in a VVER-1000 reactor using Monte Carlo simulations. He discovered that after 10.5 years of irradiation, more than 90% of ^{103}Rh had been burned, and the sensitivity dropped to 10% of its initial value. Additionally, the burnup led to a non-uniform radial density distribution in the emitter, with higher burnup rates in the outer layers compared to the inner ones [?]. Hyunsuk Lee proposed a new sensitivity calculation model based on Monte Carlo simulations and continuous-spectrum neutrons, which verified the sensitivity attenuation of Rh-SPNDs under high burnup conditions. The results were consistent with empirical data from EPRI [?]. A. Yu. Kurchenkov introduced a new method for determining the thermal power of a reactor core. By more accurately defining SPND burnup as a function of transmitted power, this method reduces errors in measuring local parameters within the reactor core [?].

As SPNDs undergo continuous burnup within the reactor core, the composition of the emitter material changes accordingly, which in turn affects the neutron capture rate and the electron escape probability of the emitter. This leads to changes in the SPND signal current. Due to the increasing complexity and diversity of emitter composition during burnup, combined with the self-shielding effect of neutrons—where burnup becomes uneven between the inner and outer layers of the emitter—the generation and escape rates of electrons within the emitter also become non-uniform. Under the influence of such multiple uncertainties, it is very difficult for traditional numerical calculations to systematically and comprehensively analyze the variation of SPND signal current with burnup. Currently, Back Propagation Neural Networks have become an important tool in nuclear technology for processing detector signals and similar data, especially in dealing with complex nonlinear relationships [?]. This study focuses on the Rhodium Self-Powered Neutron Detector and investigates the burnup and material composition of rhodium wires over time based on the Hualong One reactor. It employs a combination of Monte Carlo methods and BPNN to study the variation process of Rh-SPND signal current with burnup.

2.1 Overview of Rhodium Self-Powered Neutron Detector (Rh-SPND)

As illustrated in Fig. 1 [Figure 1: see original paper], the probe of a self-powered neutron detector typically consists of three parts: the emitter, the insulator, and the collector. Among them, the emitter is the core component of the detector and determines its fundamental characteristics. The working principle of the SPND is based on the nuclear reactions between the emitter material and neutrons, which generate free electrons [?]. These electrons pass through the insulator and reach the collector. At this point, the emitter becomes positively charged while the insulator becomes negatively charged, forming a positive and negative pole, and the electrical signal can then be transmitted via a wire.

Common emitter materials used in SPNDs include vanadium, cobalt, rhodium, and silver. Among these, rhodium has a large neutron reaction cross section and produces strong current signals, but it also burns out more quickly in the reactor. Therefore, to ensure real-time and accurate monitoring of neutron flux in the reactor core, it is necessary to conduct an in-depth study of how the signal current of Rh-SPNDs changes with burnup time.

Fig. 1 Schematic Diagram of SPND Structure

2.2 Overall Research Methodology

The overall methodology adopted in this study is structured into four major stages, which are schematically depicted in Fig. 2 [Figure 2: see original paper]. Each stage is designed to progressively model, analyze, and predict the signal current behavior of Rh-SPNDs under varying degrees of in-core burnup.

Stage 1: Burnup Simulation via Monte Carlo Modeling
In the initial stage, a detailed burnup model of the SPND emitter is constructed using Monte Carlo simulation tools. This model is used to calculate the time-dependent changes in the isotopic and elemental composition of the emitter material during extended reactor operation. The modeling considers actual reactor operating conditions, including neutron flux levels and energy spectra.

Stage 2: Sensitivity Variation Computation
In the second stage, the sensitivity of the Rh-SPND—defined as the ratio of the signal current to neutron flux—is computed for detectors with fixed geometries. The goal is to determine how this sensitivity changes as a function of burnup time, taking into account the evolving composition and geometry of the emitter.

Stage 3: Development and Training of a Predictive BPNN Model
The third stage involves building a Back Propagation Neural Network (BPNN). A comprehensive dataset, generated from the Monte Carlo simulation results, is used to train the network. The BPNN is designed to learn the complex nonlinear relationships between input variables (such as burnup time, emitter radius, and emitter layer count) and output characteristics (e.g., beta electron yield, gamma photon generation, and escape probabilities).

Stage 4: Sensitivity Prediction Across Different Conditions
The final stage involves using the trained BPNN model to predict the signal current of Rh-SPNDs of various geometries and under different levels of burnup. This predictive capability enables the estimation of detector performance over time, facilitating improved compensation strategies and ensuring reliable flux monitoring in nuclear reactors.

Through this structured and multi-layered research framework, the study aims to provide a quantitative and systematic solution to the challenge of long-term

Rh-SPND signal evolution, ensuring more accurate and robust neutron flux measurements during prolonged reactor operation.

Fig. 2 Research Methodology Framework

3.1 Generation and Calculation Method of Burnup

The emitter material within the SPND undergoes progressive neutron-induced depletion, commonly referred to as burnup, as it continuously absorbs neutrons during reactor operation. This process results in a steady decline in the SPND' s neutron sensitivity over time. To mitigate the degradation in sensitivity caused by material consumption, it is essential to accurately calculate the burnup rate of the emitter. Such calculations are vital for predicting changes in the detector' s signal current.

The burnup of a self-powered detector can be approximated using the following equation (1) [**?**]:

$$0 \exp ldf$$

Where: N represents the number of atoms in the emitter at time t; N_0 represents the number of atoms in the emitter at the initial time t_0; λ is the decay constant, with units of $(\text{year})^{-1}$ in this formula; σ_{eff} is the effective neutron capture cross-section; ϕ_n is the average neutron flux in the reactor, with units of $\text{n}/(\text{cm}^2 \cdot \text{year})$.

This mathematical formulation assumes a continuous irradiation environment and neglects short-term operational fluctuations, which is generally acceptable for long-term modeling of in-core detector behavior.

3.2 Layered Burnup Calculation Model

A significant portion of the Rh-SPND signal originates from beta electrons released during the radioactive decay of activated rhodium isotopes. Therefore, to effectively analyze the long-term signal variation, it is imperative to accurately determine the material composition of the emitter at various stages of burnup. This, in turn, necessitates a high-resolution spatial model of the emitter.

The emitter typically features a cylindrical geometry, and due to neutron self-shielding effects, the burnup distribution is inherently non-uniform across the emitter' s radial profile. Over time, the outer layers of the emitter absorb more neutrons, leading to higher local burnup rates than the inner regions. This spatial discrepancy alters not only the nuclide distribution but also the distribution of beta electron generation and escape probabilities across the emitter' s cross-section.

To capture this radial heterogeneity, a layered model is employed, as depicted in Fig. 3 [Figure 3: see original paper]. The emitter is divided into multiple concentric layers, with each layer analyzed independently for its burnup level and associated electron escape characteristics. This modeling strategy enhances computational precision and enables more accurate estimation of the detector' s net current response.

Fig. 3 Schematic Diagram of Emitter Layering

Given that the SPND operates directly within the reactor core environment, the burnup simulation must be tailored to reflect realistic operating conditions, including reactor-specific neutron flux spectra and geometry. In this study, the Hualong One Pressurized Water Reactor (PWR) is selected as the reference model. Fig. 4 [Figure 4: see original paper] presents the schematic diagram of a Hualong One fuel assembly, along with the neutron energy spectrum within the instrumentation channel where the SPND is embedded.

The rhodium wire is modeled within this guide tube, and burnup simulations are conducted using the Monte Carlo N-Particle (MCNP) transport code, utilizing the burn card feature to track isotopic depletion and transmutation over time. This allows for the quantification of both elemental composition and nuclide inventory after specified burnup intervals.

Fig. 4 Hualong One Fuel Assembly Model and Neutron Energy

Using a rhodium wire with a radius of 0.4 mm as the representative case, the material and geometric parameters used in the simulation are summarized in Table 1 . The neutron energy spectrum derived from Fig. 4 is applied as the input source, and the neutron flux in the core is set to 1$×10^{14}$ n/($cm^2 \cdot s$). Based on these inputs, the MCNP code is used to simulate the burnup evolution of the emitter over a 10-year period. The resulting data are plotted in Fig. 5 [Figure 5: see original paper], which illustrates the spatial variation in burnup across the emitter radius.

The variable R/R_0 is defined, where R_0 is the total radius of the emitter and R is the distance from the emitter's center. The plot shows that as R/R_0 increases, burnup also increases–confirming the non-uniform radial behavior due to neutron attenuation in the material. After 10 years, the outermost layer exhibits a burnup level that is 66% higher than that of the innermost layer. This significant discrepancy highlights the necessity of using layered models to accurately account for spatial effects in emitter degradation and signal prediction.

Table 1 SPND Geometry and Material Parameters

Materials	Density (g/cm^3)	Radius (cm)	Length (cm)
Emitter			
Insulator	103Rh Al_2O_3		
Collector	Inconel-600		

Fig. 5 Burnup of Rhodium Wire with 0.4 mm Radius

3.3 Material Composition of Rh-SPND After a Certain Burnup Duration

The burnup card output from MCNP provides detailed information on the nuclide composition of the Rh-SPND after specified irradiation periods. For ^{103}Rh, a key emitter isotope, the full reaction chain is shown in Fig. 6 [Figure 6: see original paper], which includes isotopic transmutation and radioactive decay pathways such as (n, γ), (n, α), (n, p), (n, nα), and β-decay processes.

These reaction chains result in a wide variety of secondary nuclides, some of which are radioactive and continue to contribute to signal current via their own decay emissions. Using the rhodium wire with a radius of 0.4 mm, the mass fractions of various nuclides are tracked over time, as shown in Fig. 7 [Figure 7: see original paper].

To assess the impact of burnup on signal current, particular attention is paid to nuclides that exhibit both high abundance and significant neutron cross-sections, as these are most likely to influence the overall performance of the SPND. The primary radioactive products of ^{103}Rh burnup include ^{104}Rh, ^{105}Rh, ^{103}Ru, ^{99}Tc, and ^{100}Tc, with half-lives ranging from seconds to hundreds of thousands of years. However, ^{100}Tc is excluded from consideration due to its extremely low abundance (below 1$×10^{-10}$).

In terms of stable and long-lived isotopes, nuclides such as ^{104}Pd, ^{105}Pd, ^{106}Pd, and ^{104}Ru remain present in considerable amounts post-burnup. These isotopes directly affect the mass, density, beta emission rate, and electron escape behavior of the emitter and must therefore be accounted for in any accurate modeling of the Rh-SPND' s long-term response.

Fig. 6 Reaction Chain of ^{103}Rh and Neutrons

Fig. 7 Time-Dependent Mass Fraction of Various Nuclides

4 Computational Model for the Sensitivity Variation of Rh-SPND with Burnup Time

The electrons contributing to the Rh-SPND signal current can be categorized into the following components: (a) Electrons emitted from the decay of ^{104}Rh and ^{104}mRh, which are produced through the (n, γ) reaction between neutrons and rhodium. This portion of the current is referred to as delayed current, and it constitutes the primary component of the Rh-SPND signal. (b) Electrons generated via photoelectric effect, Compton scattering, and pair production caused by gamma photons produced in the (n, γ) reaction between neutrons and rhodium. This portion is called prompt current, and it contributes a smaller fraction. (c) Electrons generated by the interaction of reactor gamma photons with the Rh-SPND through photoelectric effect, Compton scattering, and pair production. This component is considered interference current and must be subtracted from the total current.

The sensitivity of a self-powered neutron detector is defined as the ratio of the Rh-SPND signal current to the neutron flux surrounding the detector:

$$S = \frac{I}{\phi_n} = \frac{I_b + I_g}{\phi_n}$$

Where: I denotes the signal current, S is the sensitivity coefficient of the Rh-SPND, ϕ_n is the neutron flux; I_b is the current generated by beta electrons, I_g is the current generated by gamma radiation.

4.1 Computational Model for the Variation of Delayed Current with Burnup

The delayed current is mainly produced from the decay of ^{104}Rh and can be expressed as:

$$I_b = e \cdot R_b \cdot P_e^b$$

Where: e is the elementary charge, valued at 1.60$\times10^{-19}$ C; R_b represents the generation rate of beta electrons within the entire emitter; P_e^b denotes the escape probability of the electrons.

4.1.1 Variation of Neutron Capture Rate with Burnup Time

To investigate the spatial variation of neutron absorption in the emitter, a rhodium wire with a radius of 0.4 mm is analyzed. Due to the neutron self-shielding effect, neutron flux is attenuated as it penetrates radially inward, leading to non-uniform burnup across the emitter' s cross-section. To quantitatively model this phenomenon, the rhodium wire is divided into 10 concentric layers, with layer 1 located at the central axis and layer 10 on the outermost surface. The burnup level and composition of each layer are derived from prior Monte Carlo simulations. As shown in Fig. 8 Figure 8: see original paper, there is a pronounced difference in neutron capture rate across layers. After 10 years of irradiation, the innermost layer shows an 18% change, while the outermost layer experiences a 96% change. This gradient highlights the strong influence of spatial position on neutron-induced transmutation.

Fig. 8(b) presents each layer' s contribution to the total neutron capture rate as a function of time. The outermost layer' s contribution declines steadily, while the inner layers contribute increasingly over time. This shift in neutron absorption leads to a gradual inward migration of the beta electron production centroid, which must be considered in dynamic sensitivity modeling.

Fig. 8 Variation of neutron capture rate with burnup time, R_0 refers to the radius of the rhodium wire (0.4 mm), R refers to the distance from the axis of the rhodium wire.

4.1.2 Escape Probability of Beta Electrons

The escape probability of electrons in the emitter is related to the electron's position, energy, and the material composition of the emitter. Still taking a rhodium wire with a radius of 0.4 mm as the research object, it is divided into 10 layers. The calculation uses the Geant4 program, with the material composition of the rhodium wire in different layers calculated in Fig. 7 as input data.

When calculating the escape probability of beta electrons, it is necessary to set the electron energy. Beta electrons are mainly generated by the decay of ^{104}Rh. However, after the rhodium wire has been burned for a period of time, other radioactive nuclides such as ^{105}Rh, ^{103}Ru, and ^{99}Tc are also produced. Table 2 lists the variation of the activity of these 4 radioactive nuclides with burnup time. According to the data in the table, the activity of ^{104}Rh is at least 4-5 orders of magnitude higher than that of the other four radioactive nuclides. This magnitude difference allows the influence of radioactive nuclides other than ^{104}Rh to be excluded when setting the beta electron energy in Geant4.

Fig. 9 [Figure 9: see original paper] shows the escape probability of beta electrons for different burnup times and different layers. It can be seen from the figure that the change in material composition caused by rhodium wire burnup has basically no effect on the escape probability of beta electrons. This is because when electrons escape from the inside of the emitter to the emitter surface, their energy loss is mainly through ionization and radiation. When the electron energy remains unchanged, the energy loss caused by ionization and radiation is mainly related to the atomic number and density of the target material. The atomic number of the products after rhodium burnup varies within a range of $\pm$2, and the density change of the emitter is also very small. Therefore, the change in material composition caused by burnup has basically no effect on the escape probability of beta electrons. This conclusion allows us to decouple escape probability from burnup composition in subsequent modeling steps.

Table 2 Radioactivity of Burnup-Produced Radioactive Nuclides

Burnup time (year)	104Rh	Radioactive activity (Ci)	103Ru	105Rh	99Tc
	2.60E+02	7.72E-04	6.09E-03	5.52E-12	
	2.48E+02	7.47E-04	1.06E-03	1.03E-11	
	2.30E+02	6.84E-04	3.19E-03	1.47E-11	
	2.13E+02	4.34E-04	6.76E-03	1.93E-11	
	2.06E+02	1.00E-03	3.31E-03	2.44E-11	

Burnup time (year)	104Rh	Radioactive activity (Ci)	103Ru	105Rh	99Tc
	1.90E+02	5.75E-04	6.52E-03	4.96E-11	
	1.82E+02	6.87E-04	5.63E-03	5.00E-11	
	1.79E+02	4.34E-04	1.06E-02	6.62E-11	
	1.62E+02	9.10E-04	1.68E-02	7.07E-11	
	1.55E+02	5.95E-04	4.85E-02	1.21E-10	

Fig. 9 Beta electron escape probability

4.2 Computational Model for the Variation of Prompt Current with Burnup

Prompt current is generated by electrons produced through the photoelectric effect and Compton scattering when gamma rays interact with the emitter. It can be expressed as:

$$I_g = e \cdot P_g \cdot R_e \cdot P_{ee}$$

Where: e is the elementary charge, P_g denotes the probability of gamma ray production from neutron interactions within the emitter, R_e denotes the probability that gamma rays generate electrons in the emitter, P_{ee} denotes the escape probability of electrons generated by gamma rays.

4.2.1 Variation of Gamma Ray Yield with Burnup Time

The fast response part in the signal current of Rh-SPND is generated by the reaction of gamma photons with the detector. This part of the current also changes with burnup time, so it also needs to be calculated. The prompt gamma rays in Rh-SPND are mainly generated by the (n, γ) reaction between neutrons and the materials of the Rh-SPND. Additionally, radioactive nuclides also emit gamma rays during decay due to energy level transitions. This part of the gamma rays belongs to delayed gamma rays and accounts for a relatively low proportion. Since the reaction cross-sections of the collector and insulator materials with neutrons are low, only the variation of gamma ray yield from the emitter with burnup time is considered. Fig. 10 Figure 10: see original paper shows the gamma photon spectrum in different layers of the emitter after 1 year of burnup. Fig. 10(b) shows the variation of gamma photon generation rate with burnup time. It can be seen that the gamma photon generation rate continuously decreases with burnup time, with the first layer decreasing the slowest (21% decrease from year 1 to year 10) and the tenth layer decreasing the fastest (25% decrease from year 1 to year 10). Compared to the huge difference in neutron capture rate between inner and outer layers, the change in gamma photon generation rate between inner and outer layers is basically consistent. This is because the neutron capture rate is only the capture rate of neutrons by ^{103}Rh, while the gamma photon generation rate is generated by the reaction of the entire emitter material with neutrons, including gamma photons generated from (n, γ) reactions of other nuclides produced after a certain burnup time. The yield of delayed gamma rays accounts for about 1.2% of the total gamma rays, and the contribution of electrons generated by their reaction with the detector to the total current signal can be neglected. Therefore, the variation of delayed gamma rays with burnup time is not considered.

Fig. 10 Variation of gamma photon generation rate with burnup time

4.2.2 Variation of Probability of Electron Generation by Gamma Rays with Burnup

The probability of gamma rays interacting with the emitter to generate electrons is mainly affected by the electron energy and the atomic number of the target material. Burnup of the emitter changes its material composition, affecting the electron generation rate. Therefore, it is necessary to calculate the variation of the probability of electron generation by gamma rays with burnup time. As shown in Fig. 11 [Figure 11: see original paper], as burnup time increases, the electron generation rate continuously increases, with the innermost layer showing the largest change and the outermost layer' s electron generation rate remaining basically unchanged; the electron generation rate varies significantly between different layers. As R/R_0 increases, the electron generation rate continuously decreases. This is because the path length gamma photons travel in the emitter is different; the larger R/R_0, the shorter the path, the fewer collisions with the emitter, and thus fewer electrons are generated.

Fig. 11 Trend of the probability of electron generation by gamma rays with burnup time

4.2.3 Escape Probability of Electrons Generated by Gamma Rays

Prompt gamma rays interact with the emitter through Compton effect and photoelectric effect to generate electrons, forming the instantaneous response current. The escape probability of these electrons is affected by the gamma ray spectrum and their generation position within the emitter. Using the spectrum in Fig. 10(a) as the input source, the electron escape rate is calculated. Fig. 12 Figure 12: see original paper shows the electron spectrum generated by gamma photons interacting with the emitter through photoelectric effect, Compton effect, and electron pair effect. The escape probability of electrons generated by gamma rays is shown in Fig. 12(b). Similar to the situation with beta electron escape probability, the larger the R/R_0 value, the greater the electron escape probability. Moreover, the change in rhodium wire composition due to burnup time has basically no effect on the electron escape probability. The reasons for this have been discussed in the section on beta electron escape probability and will not be repeated here.

Fig. 12 Compton electron, photoelectron spectrum; (b) Compton electron, photoelectron escape probability

4.3 Influence of Gamma Rays in the Reactor on Rh-SPND Signal Current

Gamma rays within the reactor originate from nuclear fuel fission and reactions between neutrons and other materials in the reactor. Changes due to Rh-SPND burnup do not affect their spectrum or flux. Therefore, this section mainly discusses the electron generation rate from the interaction of gamma rays within the reactor with the emitter at different burnup times. The gamma photon spectrum within the reactor is shown in Fig. 13 Figure 13: see original paper. Using this as the input source, the electron generation rate is calculated. Taking the probability of electron generation from the interaction of reactor photons with the emitter before rhodium wire burnup as the baseline, the change in electron generation rate due to emitter burnup at different times is calculated. The calculation results are shown in Fig. 13(b) [?]. The deviation in electron generation rate due to burnup is within $±$4%, while the signal current generated by gamma rays within the reactor accounts for 5%-8% of the total current signal [?]. The error in this part of the current caused by burnup will contribute no more than 0.3% to the total Rh-SPND current signal. To improve computational efficiency and reduce unnecessary calculations, the error in this part of the current caused by burnup will not be considered in subsequent predictive model calculations.

Fig. 13 (a) Reactor gamma ray spectrum; (b) Ratio of electron generation rate in the emitter from reactor gamma photons at different burnup times relative to the initial composition

5.1 Introduction to BP Neural Network

The Backpropagation Neural Network is a type of multi-layer feedforward network trained according to the error backpropagation algorithm [?]. The characteristics of this network are its nonlinear mapping capability and flexibility, allowing its network structure to be adjusted according to the requirements of the problem. The BP neural network consists of an input layer, hidden layer(s), and an output layer, where the hidden layer can be one or more layers [?]. Fig. 14 [Figure 14: see original paper] shows the structure of a typical three-layer BP neural network. X_i is the input layer, w_{ij} is the weight coefficient from the input layer to the hidden layer, θ is the threshold of the hidden layer, h is the activation function of the hidden layer, w_{jk} is the weight coefficient from the hidden layer to the output layer, a is the threshold of the output layer, f is the activation function of the output layer, and O is the actual output value.

Fig. 14 Structure of BP Neural Network

5.2 BP Neural Network Model Training

Establishing a prediction model based on BPNN requires a foundation. First, a certain amount of training data needs to be calculated through preliminary Monte Carlo models. Only by training the BPNN with this training data can the desired prediction model be obtained. In the study of SPND signal current variation with burnup time, the actual relationship needed is the neutron sensitivity of detectors of different sizes at different burnup times. Therefore, for the BPNN, the input layer data are burnup time, emitter radius, and the number of emitter layers. The output layer data are neutron capture rate, beta electron escape rate, gamma photon generation rate, probability of electron generation by gamma photons, and escape rate of electrons generated by gamma photons. The purpose of this work is to solve for the neutron sensitivity of Rh-SPND of different sizes at different burnup times. The burnup time range is 0-10 years. To calculate the emitter material composition after burnup in more detail, the time step is set to 1 quarter (3 months). Considering differences between sizes, when layering the emitter, a step size of 0.05 mm is chosen, and the number of layers for emitters of different sizes also varies.

Training the BP neural network requires determining the number of input layer nodes, the number of hidden layers, the number of hidden layer nodes, and the number of output layer nodes. Among these, the number of input layer nodes is 3 and the number of output layer nodes is 5, which are already determined. The number of hidden layers depends on the complexity of the problem. For relatively less complex problems and a not-too-large experimental sample size, the number of hidden layers is generally 1 or 2, and should not exceed 3, otherwise overfitting may occur [**?**]. There is no theoretical guidance for choosing the number of hidden layer nodes. In deep networks, the number of nodes is usually reduced layer by layer, such as scaling down proportionally from input to output. The activation function between the hidden layer and the output layer uses the Sigmoid function [**?**], whose expression is:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The quality of the trained model is measured using the Root Mean Square Error (RMSE) [**?**]. RMSE is sensitive to outliers in the data, and its expression is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}$$

Where N is the number of samples; Y_i is the true value; $\hat{Y}_i$ is the predicted value.

The Monte Carlo program was used to simulate and calculate 520 sets of training data. Among them, 470 sets were used to train the BPNN, and the remaining 50 sets were used to test the BPNN prediction model. The initial training model parameter selection is shown in Table 3 .

The training model set first-order and second-order momentum factors. By monitoring the change in the loss function, the learning rate is automatically adjusted: if the loss function stagnates for 20 epochs, the learning rate is multiplied by 0.5 until the learning rate equals 1e-6, achieving fine-grained learning rate adjustment in the later stages of training and improving the final convergence quality of the model. Simultaneously, L2 weight regularization is added to the hidden layer to penalize large weights and prevent overfitting. In terms of training strategy, EarlyStopping is set to automatically stop training and restore the optimal weights when the validation set metric no longer improves, saving computation time while improving generalization performance.

Table 3 Initial Parameter Settings for Model Training

Initial Learning	Minimum Momentum	L2 Weight	Iterations/
Rate [0.9, 0.999]	Factor	Regularization	Epochs

5.3 Training Results

After constructing the prediction model, the neural network was optimized and trained to determine the appropriate number of hidden layers and the number of neuron nodes per layer. The usual training approach is to test different training times for different numbers of hidden layers and neuron nodes, from simple to complex structures, to find a neural network structure with a smaller RMSE value. After multiple rounds of parameter tuning and training, a three-layer structure of 64:64:64 was finally determined. Fig. 15 [Figure 15: see original paper] shows the adaptive changes of the loss function and learning rate during the training iterations. With the EarlyStopping mechanism, the model reached its optimum at Epoch 967 and stopped iterating. Fig. 16 [Figure 16: see original paper] shows the agreement between the true values and predicted values for the 5 output layers. Output1 - Output5 correspond to neutron capture rate, beta electron escape rate, gamma photon generation rate, probability of electron generation by gamma photons, and escape rate of electrons generated by gamma photons, respectively. The RMSE values for the training outputs were 0.0000158, 0.000976, 0.0000853, 0.0000983, and 0.000542, respectively. This indicates that this neural network is effective and can well reflect the mapping relationship between the parameters burnup time, emitter radius, number of emitter layers, and the neutron capture rate, beta electron escape rate, gamma photon generation rate, probability of electron generation by gamma photons, and escape rate of electrons generated by gamma photons. It can provide data support for subsequent research on the variation of Rh-SPND signal current with in-core burnup time.

Fig. 15 Adaptive Variation of Loss Function and Learning Rate During Iterations

Fig. 16 Comparison Between Actual and Predicted Values

5.4 Prediction Results of the Model for Rh-SPND Sensitivity Variation with Time

As shown in Fig. 17 [Figure 17: see original paper], the comparison results between the Monte Carlo calculated values and the predicted values from the model for the sensitivity of Rh-SPND with a rhodium wire radius of 0.4 mm. It can be seen that when the burnup time is less than 9 years, the calculated values and predicted values are basically identical. When the burnup time is greater than 9 years, the predicted values are larger than the calculated values, showing a certain deviation. Overall, the prediction model can achieve accurate prediction of Rh-SPND sensitivity variation with time. Fig. 18 [Figure 18: see original paper] shows the prediction results of the model for the sensitivity of Rh-SPND with rhodium wire radii ranging from 0.1 mm to 1.0 mm over burnup time. As burnup time gradually increases, the linearity of the Rh-SPND sensitivity change trend weakens, and the rate of change gradually decreases. Moreover, within 10 years of burnup time and at a neutron flux rate of 1$×10^{14}$ n/($cm^2 \cdot s$), the smaller the radius of the rhodium wire, the larger the range of its sensitivity change. Specifically, the sensitivity of Rh-SPND with a rhodium wire radius of 0.1 mm decreases by 51.3%, while that with a radius of 1 mm decreases by 25.2%. The main reason for this difference is the neutron self-shielding effect.

Fig. 18 reveals the variation pattern of Rh-SPND sensitivity with burnup time. To achieve real-time and accurate monitoring of core neutron flux, it is very necessary to perform time correction on the sensitivity of Rh-SPND. Moreover, this correction must consider the radius of the emitter and the neutron flux level within the reactor.

Fig. 17 Comparison of Monte Carlo and Predicted Sensitivity for 0.4 mm Rhodium Wire

Fig. 18 Variation of Rh-SPND Sensitivity with Burnup Time

6 Conclusion

This study presents a comprehensive investigation into the long-term variation of signal current in Rhodium Self-Powered Neutron Detectors (Rh-SPNDs) under extended in-core burnup conditions. A combination of Monte Carlo simulations, layered material modeling, and neural network-based prediction was employed to develop a high-accuracy, data-driven sensitivity model.

The key conclusions can be summarized as follows:

1. The emitter material composition undergoes significant changes during long-term irradiation due to neutron-induced transmutation and radioactive decay. These changes affect both beta and gamma electron generation and escape behavior.
2. A layered burnup model reveals that the burnup rate is radially non-uniform, with the outermost layers experiencing up to 66% higher depletion compared to the core. This gradient leads to a gradual shift in beta electron production toward the emitter center over time.
3. The contribution of prompt current and reactor gamma-induced interference current to the total SPND signal was evaluated. While prompt gamma electrons show some sensitivity to burnup, their overall effect remains limited. Reactor gamma-induced electrons contribute less than 0.3% of the signal variation and can be neglected for practical prediction purposes.
4. A Back Propagation Neural Network (BPNN) was developed to predict SPND sensitivity across different burnup durations and emitter geometries. The model demonstrated excellent agreement with Monte Carlo simulation results, with a maximum relative error below 2.3%.
5. The model predictions show that smaller emitter radii lead to greater sensitivity degradation, with a 51.3% decrease for 0.1 mm wires and 25.2% for 1.0 mm wires over 10 years. This highlights the necessity of geometry-based compensation or replacement strategies for long-term SPND deployment.

In conclusion, this study provides a reliable framework for predicting Rh-SPND performance degradation due to burnup. The developed BPNN model, grounded in physical simulation and enriched by data-driven learning, offers a practical tool for optimizing SPND deployment and calibration in real-world nuclear reactors. The methodology is generalizable and may be extended to other detector materials and configurations in future work.

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Note: Figure translations are in progress. See original paper for figures.