2025 IEEE/SICE International Symposium on System Integration (SII)
January 21-24, 2025, Munich, Germany

Estimation of Radiation Source Distribution in RPV Based on Prior Knowledge of Fuel Debris Spreading

Hiroki Matsuno and Hanwool Woo

***Abstract*— This study proposes a novel method for estimating radiation source distribution in a reactor pressure vessel (RPV), especially focusing on the fuel debris retrieval at the Fukushima Daiichi Nuclear Power Plant. Before the fuel debris retrieval, it is necessary to grasp the internal situation of a primary containment vessel (PCV). Our research group is planning to insert an investigation unit from the top of the PCV and measure radiation using non-directional gamma-ray detectors. The proposed method defines the bottom of the RPV as two-dimensional grids and estimates the radiation source distribution. The proposed method consists of four steps: database construction, choosing candidates from the dataset, comparing the candidates with the prior knowledge, and additional measurements. Simulation experiments demonstrate that the proposed method is possible to accurately estimate the radiation source distribution in the RPV with a limited number of measurements.**

I. INTRODUCTION

In decommissioning of the Fukushima Daiichi Nuclear Power Plant, fuel debris retrieval tasks in the PCV are still under consideration [1], [2]. The tasks are significant challenges due to the unknown situation in the PCV including the radiation source distribution. A dry method is one of fuel debris retrieval methods for decommissioning [2], and our research group is planning to insert an investigation unit from the top of the PCV and measure radiation using non-directional gamma-ray detectors. The internal situation of the PCV has been changed in unknown ways, and it is difficult to determine measurement locations of radiation under uncertain environment with lack of information

Shi et al. developed digital technology to enable inverse estimation of radiation sources and counter measures in simulation [3], [4]. This study aims to clarify the position of high-dose radiation sources, and the authors proposed a derivative model of machine learning called as Least Absolute Shrinkage and Selection Operator (LASSO). This method performs inverse estimation through simulation. However, this method cannot be used in unknown environments since environment information is required for training the model. Newaz et al. proposed a method to identify high-dose areas using a Hexagonal Tree in an environment where multiple sources exist in a wide unknown area [5]. This method showed superior performance in terms of total sampling path length and convergence time for hotspot identification compared to the conventional RIG-tree algorithm. Chao et al. estimated the radiation source distribution using the maximum-likelihood estimation method optimized by gradient descent [6]. However, these methods require numerous measurements despite the difficulty of long-term measurements due to high radiation doses.

H. Matsuno and H. Woo are with the Department of Mechanical Systems Engineering, Kogakuin University, 2665-1 Nakano, Hachioji-si, Tokyo, Japan {am24066, at13710}@ns.kogakuin.ac.jp

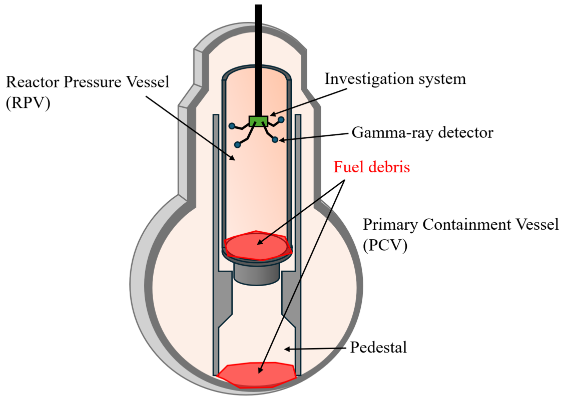

Fig. 1. Proposed system for investigation in RPV: the system is inserted to the top of the PCV after removing the upper structure of the PCV. Our system has robotic arms with non-directional gamma-ray detectors, and the detectors can be placed anywhere within reach of the arms.

Based on the above situations, this study proposes a method to estimate the radiation source distribution in the RPV using non-directional gamma-ray detectors. Figure 1 represents our investigation system and expected locations of fuel debris. Based on the previous investigation results [7], [8], fuel debris are probably distributed in the RPV and pedestal. It illustrates how the melted nuclear fuel has broken through the bottom of the RPV after the accident, accumulating inside the pedestal and partially leaking outside the pedestal. While fuel debris distributed in the pedestal was confirmed in a previous investigation [9], fuel debris inside the RPV are still unconfirmed. Our research group is planning to insert an investigation unit from the top of the RPV after removing the upper structure of the PCV, and the system measures radiation using gamma-ray detectors and internal structures using cameras. Due to the high-dose environment, long-term measurements are difficult. Therefore, it is necessary to estimate the radiation source distribution with a small number of measurements.

To overcome this limitation, our approach is to use prior knowledge of fuel debris melt spreading. It is possible to analyze the flow of fuel debris spread through numerical simulations based on the structural information of internal facilities before the accident [10]. Although there is a possibility that the actual distribution may differ from the expectation, it is possible to estimate the distribution of radiation sources with

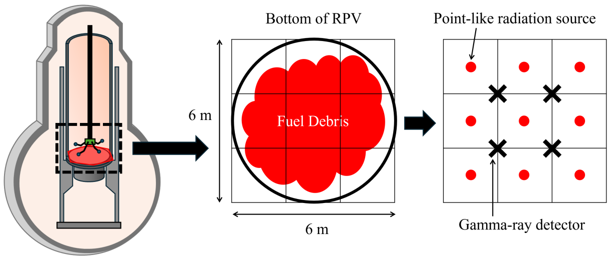

Fig. 2. Problem definition: The proposed method defines the bottom of the RPV as two-dimensional grids. A total of nine grids by dividing a 6 m × 6 m area into 3 × 3 grids. Each grid has a point-like radiation source. The proposed system is possible to simultaneously measure gamma-rays at four locations.

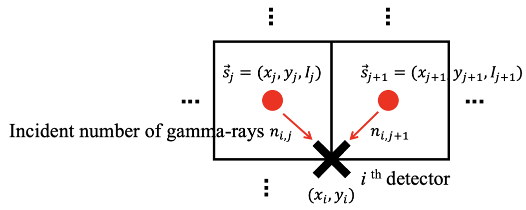

Fig. 3. Gamma-ray measurement: The j^{th} point-like source can be represented as $\vec{s}_j = (x_j, y_j, I_j)$. x_j and y_j are the position of the j^{th} radiation source, and I_j is the radiation intensity. The measurement value of i^{th} detector is determined by adding up the incident number from all radiation sources.

fewer measurements by using the prior knowledge. We aim to construct an estimation method that can cope with cases where the actual source distribution differs from the prior knowledge. Through simulations, it is demonstrated that the proposed method can accurately estimate the radiation source distribution with fewer measurements.

II. PROPOSED METHOD

Although the specific distribution of radiation sources in the RPV is unclear, it is expected to be distributed at the bottom of the RPV. The proposed method defines the bottom of the RPV as two-dimensional grids and estimates the distribution of radiation sources as shown in Fig. 2. A total of nine grids by dividing a 6 m × 6 m area into 3 × 3 grids. Although radiation sources are continuously distributed on a two-dimensional plane, this study assumes that they exist as a point source at the center of each grid. The unit of radiation intensity is MBq, and the intensity is set within a range from 0 MBq to 5 MBq.

The proposed method consists of three steps: database construction, choosing candidate distributions from the dataset and comparing them with the prior knowledge, and additional measurements.

A. Database Construction

As the first step of the proposed method, a database of all distribution cases are constructed. We place nine sources on 3 × 3 grids and vary the intensity of each source in six levels from 0 MBq to 5 MBq. Then, a total of 6^9 distribution cases are considered. Our investigation system has four robotic arms with non-directional gamma-ray detectors, therefore, the incident number of gamma-rays can be obtained at four positions simultaneously. The first gamma-ray measurements are conducted at predetermined positions. Then, the measurement values of each detector at the predetermined positions for all distribution cases are calculated and saved as the database. Figure 3 shows the aspect of the gamma-ray measurement. Assuming that there is a point-like source, $\vec{s}_j = (x_j, y_j, I_j)$, x_j and y_j represent the position of the j^{th} radiation source, and I_j is the radiation intensity. The incident number of i^{th} detector with the detector area A is represented as

$$n_{i,j} = \frac{A I_i}{4\pi\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}, \tag{1}$$

$$n_i = \sum_{j=1}^{N} n_{i,j}, \tag{2}$$

where N is the number of point-like sources, and (x_i, y_i) represents the position of i^{th} detector. As the proposed investigation system has four detectors, the measurement value, $\vec{m}_k = (n_{1,k}, n_{2,k}, n_{3,k}, n_{4,k})$, can be defined with respect to one distribution case, $\vec{d}_k = (\vec{s}_{1,k}, \vec{s}_{2,k}, \ldots, \vec{s}_{N,k})$. k is the index of radiation sources distribution cases. It is important to note that similar measurement values can be obtained for different distributions.

B. Choosing Candidates from Database and Comparing with Prior Knowledge

The first measurement is conducted at the predetermined positions in the real environment, and the measurement value, $\vec{m}_r$, is obtained. By comparing the measurement values, $\vec{m}_r$, with the database, $\vec{m}_k$, the candidate distributions can be determined. Considering that the measurement values may contain errors, we define a tolerance range as ± 0.1 MBq.

Although it is possible to narrow down the number of candidate groups, the possibility of determining just one is low due to the small number of measurement points. To overcome this limitation, the prior knowledge through numerical simulation is applied. The numerical simulation is conducted from information at the time of the accident and internal structure information. As the details of the simulation are outside the scope of this study, the description will be omitted. The proposed method leaves only candidates whose error of each source from the prior knowledge is 2 MBq. However, the possibility that multiple candidates exist after the process still remains.

C. Additional Measurements

To evaluate the remaining candidates and leave only one case, additional measurements are conducted at the different positions from the first measurement. The proposed method determines the measurement positions where are possible to maximize the difference between candidate distributions.

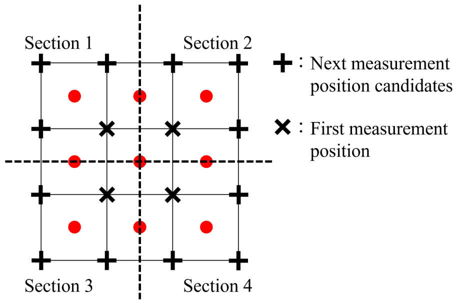

Fig. 4. Additional measurements: the proposed method divides the grids vertically and horizontally into two sections and selects the point with the maximum standard deviation in each section to determine four additional measurement points. $\times$ represents the first measurement positions, and + is the next measurement position candidates.

Although the proposed system can locate the detectors at any position by moving the robotic arms, the proposed method defines the intersections of the girds as additional measurement positions and selects the best position among the intersections. Specifically, the proposed method expects the measurement values at each intersection for each candidate distribution, and the standard deviation of measurements are calculated at each intersection. The intersection with the maximum standard deviation is selected as the next measurement point. This allows to choose points that can most effectively distinguish between the candidate distributions.

Figure 4 represents how to decide the next measurement position. The proposed method divides the grids vertically and horizontally into two sections and selects the point with the maximum standard deviation in each section to determine four additional measurement points. The next measurement position is determined as

$$\underset{l}{\operatorname{argmax}} \sqrt{\frac{1}{K}\sum_{k=1}^{K}(n_{l,k}-\bar{n}_k)^2}, \tag{3}$$

where l is the index of the next measurement positions in each section, K is the number of the remaining candidate distributions, $n_{l,k}$ is the incident number of gamma-rays at the l^{th} measurement position with respect to the k^{th} candidate distribution, and $\bar{n}_k$ is the average incident number of gamma-rays with respect to the k^{th} candidate distribution. This approach enables efficient narrowing down while covering the entire area. The proposed method calculates the likelihood of the candidates, and the best one is selected as a final estimation result.

III. EXPERIMENTS

To verify the effectiveness of the proposed method, simulation experiments were conducted. Figure 5 represents an example of simulations: (a) is the ground truth, and (b) is the estimation result with the proposed method. Nine point-like radiation sources were located at the center of each grid. Initial measurements were conducted at the predetermined four positions. The performance of the proposed method largely depends on the accuracy of the prior knowledge.

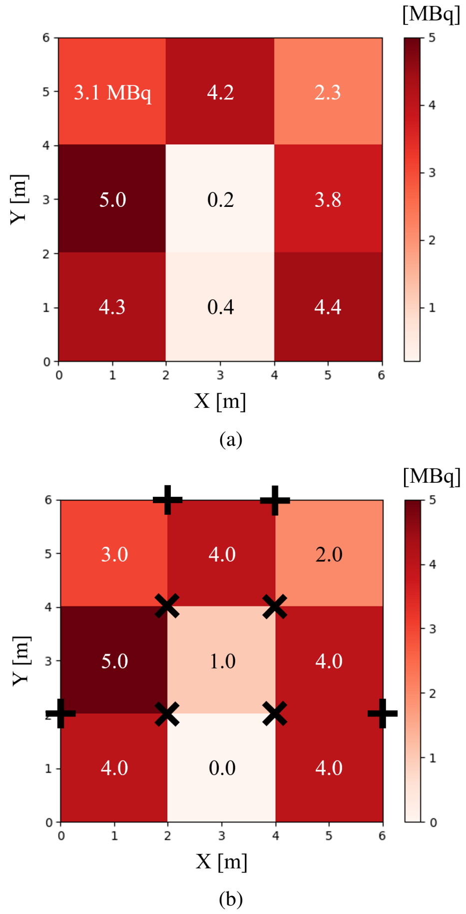

Fig. 5. Example of simulations: (a) shows the ground truth, and (b) is the estimation result with the proposed method. $\times$ represents the initial measurement positions, and $+$ is the additional measurement positions. Colors depict the intensity of the radiation sources. Values in the grids represent the radiation intensity.

In this example, the prior knowledge was generated by randomly adding 30 % errors to the radiation intensity of the ground truth. Through choosing candidates from the database and comparing with the prior knowledge, the number of candidates was reduced to 14. Then, additional measurement positions were determined as shown in Fig. 5 (b). $\times$ represents the initial measurement positions, and $+$ is the additional measurement positions. Colors and values in the grids represent the radiation intensity. The average error in radiation intensity was 0.3 MBq. It is confirmed that the proposed method successfully estimated the distribution compared to the ground truth.

As mentioned in the above description, the performance of the proposed method largely depends on the accuracy of the prior knowledge. Therefore, we defined the error of the prior knowledge into five levels and evaluated the performance of the proposed method under each condition. A total of 100 trials were conducted under each condition. The ground truth of the intensities was randomly determined each trial. Table 1 shows the results. The prior knowledge error rate means how much the expected distribution through numerical simulation deviates from the ground truth. In the expected distribution,

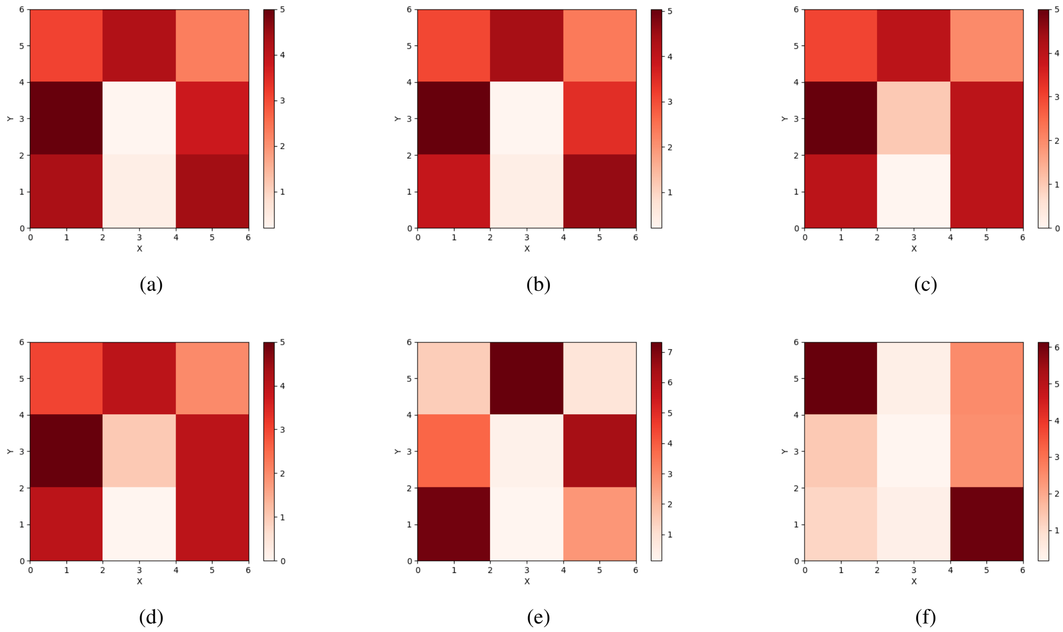

Fig. 6. Estimation results according to prior knowledge error rate: (a) shows the ground truth, (b) is the estimation result with 10 % of the prior knowledge error rate, (c) is the estimation result with 30 % of the error rate, (d) is the estimation result with 50 % of the error rate, (e) is the estimation result with 80 % of the error rate, and (f) is the estimation result with 100 % of the error rate. It is confirmed that the performance of the proposed method largely depends on the accuracy of the prior knowledge.

TABLE I
ESTIMATION ERROR OF RADIATION INTENSITY ACCORDING TO PRIOR KNOWLEDGE ERROR RATE.

Prior knowledge error rate	Estimated intensity error
10 %	0.29 MBq
30 %	0.58 MBq
50 %	0.62 MBq
80 %	0.88 MBq
100 %	1.24 MBq

the radiation intensity of each source was determined by adding an error multiplied by the specified error rate to the ground truth. The estimated intensity error represents the performance of the proposed method. The value is average of the estimated intensities of nine radiation sources. Figure 6 represents one example of the evaluation. Figure 6 (a) shows the ground truth, and the others are the estimation results according to the prior knowledge error rate. It is confirmed that as the prior knowledge error rate increased, the estimated intensity error also increased. This result shows the accuracy of the prior knowledge is significantly import. Moreover, the proposed method was possible to estimate the radiation intensity with an error within 1 MBq if the prior knowledge error rate was within 80 %. Based on the above results, the effectiveness of the proposed method was demonstrated.

IV. CONCLUSIONS

This study proposed a novel method for estimating the radiation source distribution in the RPV. The proposed method defined the bottom of the RPV as two-dimensional grids and point-like radiation sources at the center of each grid. The proposed method conducted database construction, choosing candidates from the database, comparing with the prior knowledge, and additional measurements. Through the process, the proposed method coped with cases where the actual source distribution differed from the prior knowledge. Through simulations, it was demonstrated that the proposed method can accurately estimate the radiation source distribution with fewer measurements.

As future works, we are planning to make the proposed method possible to estimate the radiation intensity as real numbers. This approach significantly improves the estimation accuracy of radiation intensities.

ACKNOWLEDGMENT

This work is financially supported by the Nuclear Energy Science & Technology and Human Resource Development Project (through concentrating wisdom) from the Japan Atomic Energy Agency / Collaborative Laboratories for Advanced Decommissioning Science.

REFERENCES

[1] Shin Morita, "Updated information about the methods of retrieval of fuel debris of the Fukushima Daiichi NPP", 2023. [Online]. Available: `https://www.meti.go.jp/english/earthquake/nuclear/decommissioning/pdf/20231006_d.pdf`. Accessed on: August 16, 2024.

[2] Tokuhiro Yamamoto, "Current status and plans of decommissioning of the Fukushima Daiichi Nuclear Power Plant", 2023. [Online]. Available: https://www.nrc.gov/docs/ML2321/ML23210A000.pdf. Accessed on: August 16, 2024.

[3] Wei Shi, Masahiko Machida, Susumu Yamada, Toru Yoshida, Yukihiro Hasegawa, and Koji Okamoto, "LASSO reconstruction scheme for radioactive source distributions inside reactor building rooms with spectral information and multi-radionuclide contaminated situations", Annals of Nuclear Energy, Vol. 184, 2023.

[4] Wei Shi, Masahiko Machida, Susumu Yamada, Toru Yoshida, Yukihiro Hasegawa, and Koji Okamoto, "Inverse estimation scheme of radioactive source distributions inside building rooms based on monitoring air dose rates using LASSO: Theory and demonstration", Progress in Nuclear Energy, Vol. 162, 2023.

[5] Abdullah Al Redwan Newaz, Sungmoon Jeong, and Nak Young Chong, "Fast radioactive hotspot localization using a UAV", 2016 IEEE International Conference on Simulation, Modeling, and Programming for Autonomous Robots, pp.9–15, 2016.

[6] Ziheng Chao, Ren Komatsu, Hanwool Woo, Yusuke Tamura, Atsushi Yamashita, and Hajime Asama, "Radiation Distribution Estimation with Non-directional Detector Using Plane Source Model", Advanced Robotics, Vol.36, No.4, pp.182–191, 2022.

[7] Akira Nakayoshi, Joy L. Rempe, Marc Barrachin, David Bottomley, Didier Jacquemain, Christophe Journeau, Viktor Krasnov, Terttaliisa Lind, Richard Lee, Donald Marksberry, Shinya Mizokami, Andrew Morreale, Damian Peko, Marco Pellegrini, and Jin Ho Song, "Review of Fukushima Daiichi Nuclear Power Station debris endstate location in OECD/NEA preparatory study on analysis of fuel debris (PreADES) project", Nuclear Engineering and Design, Vol.369, 2020.

[8] Masaki Kurata, Naoaki Okuzumi, Akira Nakayoshi, Hirotomo Ikeuchi, and Shinichi Koyama, "Step-by-Step Challenge of Debris Characterization for the Decommissioning of Fukushima-Daiichi Nuclear Power Station (FDNPS)", Journal of Nuclear Science and Technology, Vol.59, No.7, pp.807–834, 2022.

[9] Takuya Yamashita, Ikken Sato, Takeshi Honda, Kenichiro Nozaki, Hiroyuki Suzuki, Marco Pellegrini, Takeshi Sakai, and Shinya Mizokami, "Comprehensive Analysis and Evaluation of Fukushima Daiichi Nuclear Power Station Unit 2", Nuclear Technology, Vol.206, No.10, pp.1517–1537, 2020.

[10] Susumu Yamashita and Hiroyuki Yoshida, "Development of Numerical Simulation Method to Evaluate Molten Material Behaviors in Nuclear Reactors: Estimation of Fuel Debris Distribution in the Pedestal", Proceedings of the 26th International Conference on Nuclear Engineering, 2018.