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Utilization of Differential Die-Away System for Estimating Defect Position of Fresh Fuel Assembly Using Machine Learning Method

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1. Introduction

The Differential die-away (DDA) analysis was developed as a technology to estimate the content of specific nuclear materials (SVM) contained in cargo or radioactive waste. The DDA analysis can be used for nuclear fuel assemblies and is one of the next generation safeguards initiative's spent fuel nondestructive assay project in the United States [1]. The DDA analysis can evaluate the characteristics of spent fuel assembly using the neutron signal produced by induced fission in a target nuclear material over time using a pulsed external neutron source. For this purpose, a pulsed neutron generator source is more efficient in the change of a neutron signal more than an isotope source. When pulsed neutrons are irradiated to spent fuel, the neutron signal rises due to induced fission, and when the source is turned off, the signal decreases exponentially. The DDA system can use this signal decrease rate to estimate the characteristics of the spent fuel. In addition, the reduction in the concentration of nuclear material reduces the neutron reduction rate, and so the position of the fuel rod defect in the nuclear fuel assembly can be found.

2. Method

2.1. The differential die-away analysis

The DDA system consists of a 2.45 MeV pulsed neutron generator (NG), 5 cm thick lead shield, and 12 ^{3}He neutron detectors. Fig. 1 shows the system layout in water, and the ^{3}He detectors are wrapped in 1 cm polyethylene and have a 0.1 cm cadmium lining on the outside of the polyethylene. The count rate increases while neutrons are emitted from the NG. When NG stops emitting neutrons, the neutron count rate decreases exponentially, as shown in Equation (1).

$$C = C_0 e^{-t/\tau} \tag{1}$$

In Eq.(1), C is the count rate at time t after turn-off of NG, C_0 is the neutron count rate at which the NG stops emitting neutrons, and τ is the die-away time. The neutron count rate and τ depend on the amount of specific nuclear materials, detection position, and so on.

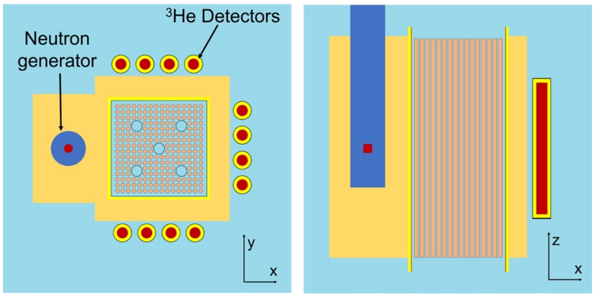

Fig. 1. Cross-sectional view of the DDA system

Fig. 2 shows the change in the neutron count rate over time when the source neutron is irradiated for 200 μs to the CE 16x16 fresh fuel assembly comprised of 4.5wt% uranium fuel rods. It was simulated using the MCNP 6.2 code. Immediately after the source is turned off, the neutron influence of the source is so significant that the characteristics of the target are not clearly revealed. After a time has elapsed after the source is turned off, the tendency to decrease neutrons in the system is evident, but the neutron count rate is low. Therefore, it is necessary to calculate the neutron reduction rate separately by dividing the time intervals after the source is turned off.

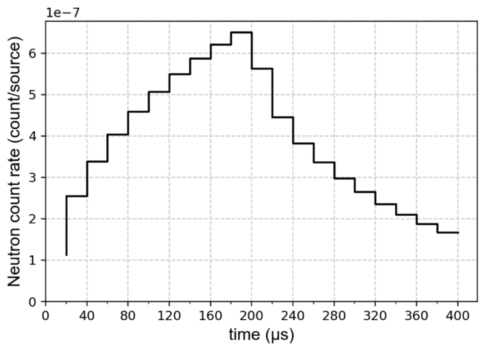

Fig. 2. Change of the neutron count rate over time

2.2. Fuel rod defect detection in assembly

Since the system is symmetrical in the y-direction and the nuclear fuel assembly to be investigated is also symmetrical, the detectors in symmetrical locations show similar signals. However, under a situation that a certain nuclear fuel rod is defective, the detectors in the symmetrical positions would show different signals, which would helpthe detection of the defect position of the fuel rod. Also, the die-away time depends on the detectors (i.e., each detector will have different die-away time) and a defect rod position gives different effects on the detectors.

In this study, the DDA system was simulated using the MCNP 6.2 code [2] for 236 cases in which one fuel rod was omitted, as shown in Fig. 3 for a CE 16x16 fresh fuel assembly with 4.5 wt% enrichment. The neutron is generated during 0~200μs, and the (n, p) reaction that occurs in the ^{3}He instrument is set to tally for 20 time intervals from 0 to 400μs in the detectors. The Monte Carlo simulations were performed such that statistical relative errors in the tallies are less than 1% in all time intervals. Afterward, the τ values were calculated using Equation (1) for the calculated signals in the 200-300 μs, 220-320 μs, 240-340 μs, 260-360 μs, 280-380 μs, and 300-400 μs time intervals for each detector. A total of 312 features were set per a case with detector signals of 20 time intervals and 6 τ values for 12 instruments. Since the position of the rod is defined as row and column, the machine learning techniques were selected for classification for each row and column. Labels were set for 16 in the row and 16 in the column, respectively. For machine learning, the scikit-learn in Phyton was used [3]. Five models were selected for the classification learning model: Gaussian Process (GP), Gradient Boost (GB), Quadratic Discriminant (QD), Stochastic Gradient Descent (SGD), and Support Vector Machine (SVM). These classification models were trained except for 48 randomly selected cases out of 236 cases. Afterward, the trained models were used to estimate the rows and columns for the defect positions of 48 test cases.

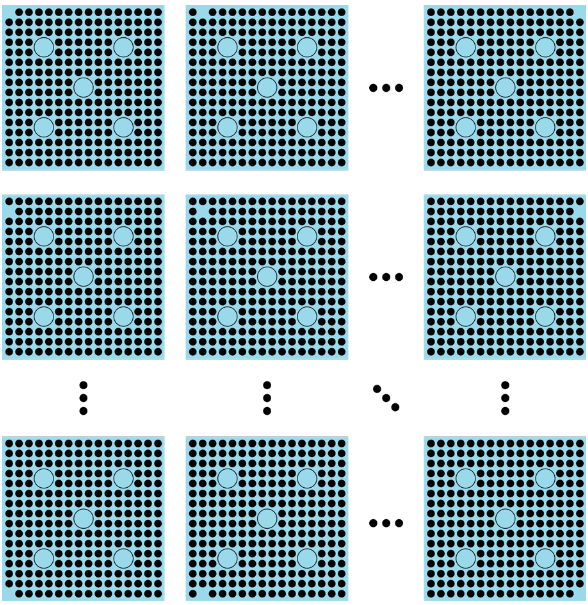

Fig. 3. The fuel rod defect cases of CE 16x16 Fuel assembly

3. Result

Fig. 4 shows the fuel rod defect position used for training and test cases.

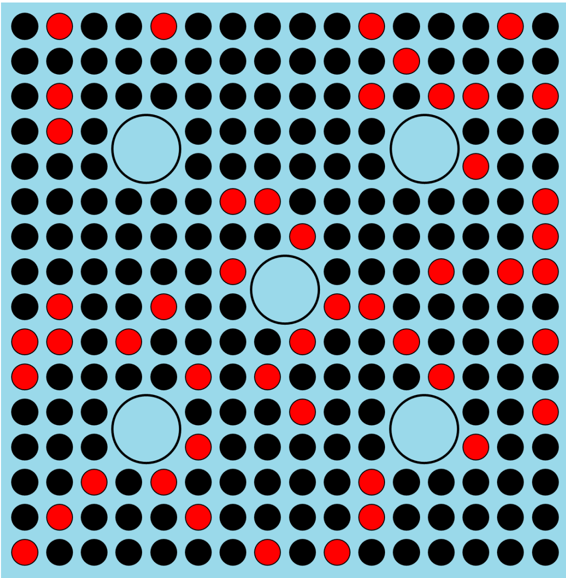

Fig. 4. Training cases defect position (black) and test cases defect position (red)

Tables I and II show the results of the prediction of rows and columns where the rod defect is. In these tables, the difference of 0 means the correct prediction of row or column while the difference of *i* means that the predicted row or column is deviated by *i* rows or columns from the correct positions. The numbers given in these tables mean the numbers of the predictions having deviations of the differences given in the second row. For example, GP correctly predicted the row and column for 22 cases of total 48 test cases (i.e., 46.8% accuracy) and 45 cases (i.e., 93.7% accuracy) if we accept one row or column deviation. Predicting rows was relatively more accurate than predicting columns. This is due to the symmetry of the detectors. Among the classification models, SVM showed the most accurate results. It was predicted with 98.9% accuracy and 91.7% for columns if we accept the deviations by one row or column.

Table I: Prediction result of row

Classification model	Difference from true value					
	0	1	2	3	4	>5
GP	22	23	3	0	0	0
GB	16	18	11	2	1	0
QD	3	10	7	5	3	20
SGD	20	19	8	1	0	0
SVM	24	23	1	0	0	0

Table II: Prediction result of column

Classification model	Difference from true value					
	0	1	2	3	4	>5
GP	22	20	2	0	3	1
GB	18	24	4	1	1	0
QD	3	7	6	13	4	15

SGD	21	23	2	2	0	0
SVM	24	20	3	1	0	0

The fuel rod defect positions were predicted using the row and column predictions and the results are shown in Table III. 1x1 means the exact prediction of the defect position while 3x3 means the correction prediction within a 3x3 fuel rod centered on the defect location.

Table III: Prediction accuracy of fuel rod defect position

Classification model	Range of defect position			
	1x1	3x3	5x5	7x7
GP	33.3%	72.9%	91.7%	91.7%
GB	6.25%	43.7%	79.2%	87.5%
QD	0.00%	4.17%	10.4%	16.7%
SGD	16.7%	54.2%	85.4%	95.8%
SVM	25.0%	68.8%	95.8%	100%

From Table III, it was shown that the Gaussian process (GP) predicted most of the defects close to the location of the defect but sometimes gave completely different predictions. In the case of the support vector machine (SVM), the prediction results were all close to the actual position. These two models correctly predicted the defect rod position with higher accuracy than 90% within 5x5 deviation and with ~70% accuracy within 3x3 deviation.

4. Conclusion

This study was conducted to expand the utilization of the DDA equipment developed as characteristic evaluation equipment for spent nuclear fuel. We investigated whether it is possible to predict the location of fuel rod defects in a fresh nuclear fuel assembly using DDA equipment. The positions of the defective fuel rod were estimated using several machine learning models. As a result, when a support vector machine was used, the location of the defect could be roughly identified. Although it was difficult to estimate the exact location, the approximate location of the defect could be determined with high accuracy. The currently used nuclear fuel assembly defect inspection equipment takes considerable time because it inspects in units of rods. If the approximate location of the defect can be determined, the examination time can be shortened. In a future study, we will study whether the defect position can be estimated in the spent fuel assembly. In addition, we will study whether the accuracy of estimating the location of the defect can be improved.

Acknowledgements

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