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# A Preliminary Study of Non-Destructive Analysis with Artificial Neural Network

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## 1. Introduction

Recently, due to the spent fuel storage is being saturated in Korea, a lot of research is being studied to transport and store the spent nuclear fuel out from reactor site. To transport and store the spent fuel, the information of the spent fuel such as burnup and amount of generated fission product is necessary. Various of Non-Destructive Analysis (NDA) techniques have been developed for the information of the spent fuel and structural integrity so far, yet its accuracy is unreliable relatively. In this study, to analyze the spent fuel information in more accurate, the Artificial Neural Network (ANN) has been proposed with NDA method.

The NDA method has been studied with NGSI-SF project about application in spent fuel analysis, and it also has been applicated in detecting nuclear material by International Atomic Energy Agency (IAEA). The NDA technique in this study requires external neutron pulse to interrogate the nuclear material in spent fuel. When external neutron source interrogates the nuclear material or spent fuel, it occurs fission neutrons in the nuclear material. Then the detectors show detected signal by fission neutrons. The signal from detector dies away after the external neutron pulse. The signal during die-away time characterizes the nuclear material. [1]

In this paper, the DDA method has been performed with ORIGEN-ARP and MCNP code. The signals have been analyzed with least-square fitting method and ANN. [2, 3]

## 2. Conditions

To analyze the fission neutron from neutron detector signal, the spent fuel and NDA technique applicated instrument has been designed with MCNP code. The spent fuel conditions have been considered as Table 1 to applicate in ORIGEN-ARP code with WH17x17 fuel assembly.

Table 1. Spent Nuclear Fuel Conditions

| IE[1] (wt%) | BU[2] (GWd/tU) | CT[3] (yr) |
|---|---|---|
| 1.5 | 15 | 0.5 |
| 2.0 | 20 | 1.0 |
| 2.5 | 25 | 2.5 |
| 3.0 | 30 | 5.0 |
| 3.5 | 35 | 10.0 |
| 3.8 | 40 | 20.0 |
| 4.0 | 45 | 30.0 |
| 4.3 | 50 | 40.0 |
| 4.5 | 55 | 50.0 |
| 5.0 | 60 | 60.0 |

IE[1]: Initial Enrichment
BU[2]: Burnup
CT[3]: Cooling Time

The average power and fuel cycles have been fixed with 40 MW/MTU and 3 cycles. The output of ORIGEN-ARP has been modified to introduced in MCNP input. As shown in Table 1, total 1000 cases of spent fuel conditions have been considered and provided for ANN in this paper. The NDA technique applicated instrument has been designed with MCNP and visualized with Vised as Figure 1 which referred the NDA instrument designed and introduced in Sweden. [1, 4]

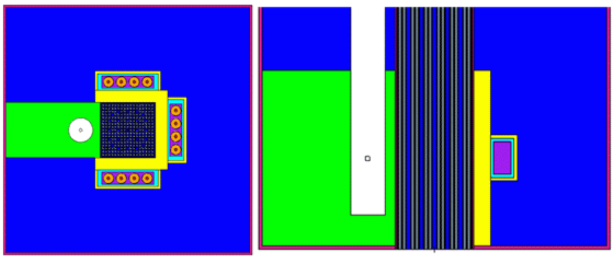

Figure 1. NDA Instrument Designed with MCNP6.2

In Figure 1, spent fuel is loaded in the center of the instrument, and the external neutron source would be given from the neutron generator with 90 micro-sec neutron pulse in Figure 1. Then, 12 numbers of He-3 neutron detectors would detect the thermal neutrons from the spent fuel.

The results of MCNP have also been modified to figure out the signals from detectors around the spent fuel. These processes from ORIGEN-ARP to signal has been automatized with python modules as Figure 2.

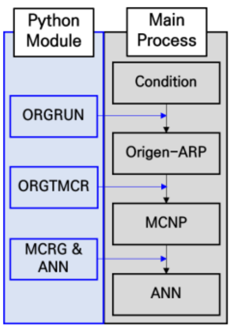


Figure 2. Calculation Process with Python Modules

With the spent fuel conditions from Table 1, 1,000 cases of inputs for ORIGEN-ARP, MCNP are created. For saving the calculation time of MCNP, calculation time has been fixed with "200 ctme" which is the calculational option of MCNP code.

## 3. Analysis

Before learning the data from the MCNP result, it is necessary to figure out the data is appropriate or not. To check the data, it is also required to check the homogeneity of the neutron source from the neutron generator. To show the homogeneity of the neutron source, the "FMESH" option of MCNP code has been utilized as Figure 3.

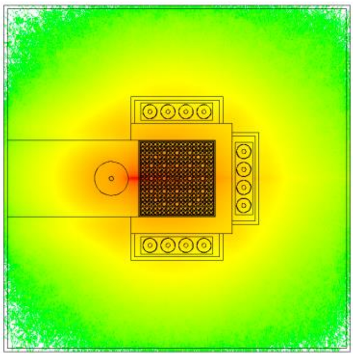

Figure 3. Neutron source from neutron generator to spent fuel in DDA instrument

Then, it is needed to figure out whether the surrounded 12 numbers of He-3 detectors get enough neutron flux and product photons by the neutrons from neutron generator. Thus, the case with IE 4.3 wt%, BU 50 GWd/MTU, and CT 10 years has been chosen to show neutron spectrum and photon production with He-3 detectors.

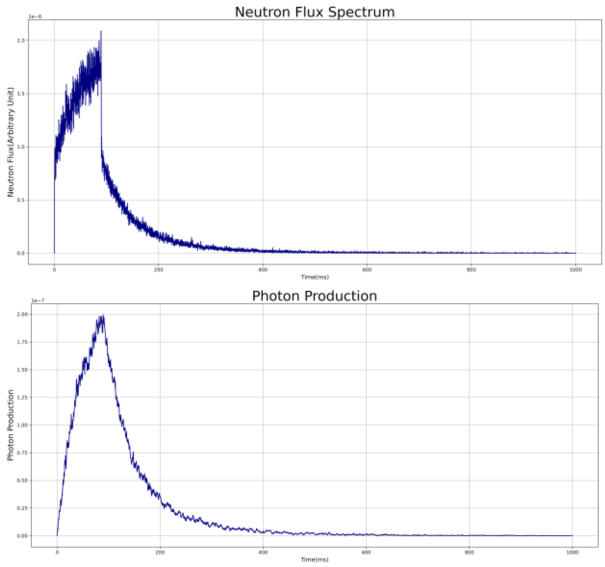


Figure 4. Neutron flux spectrum and photon production from He-3 Detectors

As shown in Figure 4, neutron spectrum shows die-away after the 90 micro-sec neutron pulse from neutron generator, and it shows almost zero value nearby 600 micro-sec. This characteristic has shown similar in photon production graph. Therefore, the main characteristics to show the 3 inputs of IE, BU, and CT will be shown between 90 to 600 micro-sec. Then, rearrange the data in range of 90 to 600 micro-sec, and calculate exponentially fitted data to compare with original graph. The fitted data and original data have been compared as Figure 5.

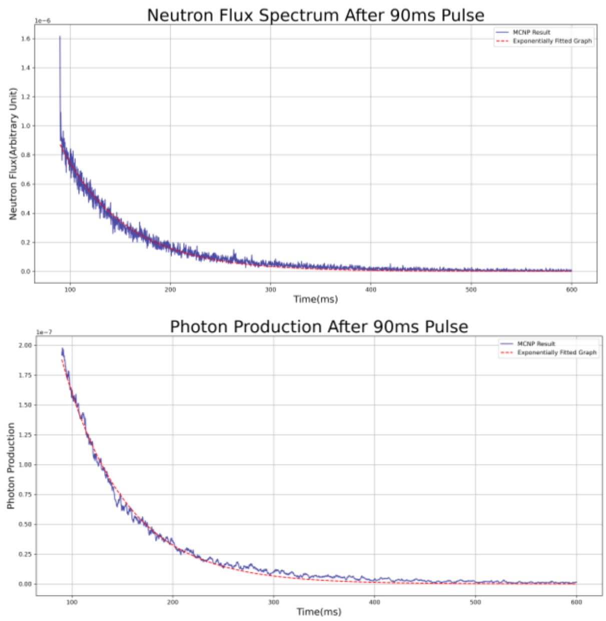


Figure 5. Comparison between exponentially fitted data(red) and original data(blue)

As shown in Figure 5, it has shown similar graph as Rossi-alpha distribution which fitted as Equation 1.

$$S(t) = Re^{-\alpha t} \quad (1)$$

In addition, the signals from the neutron detectors would be influenced by photon production result, also, as shown in Equation 1, S(t) is defined by α. Therefore, the results have been rearranged and prepared for training ANN with α value. The value α is defined as Equation 2 for calculating least square fitting.[5]

$$\alpha = a \cdot IE + b \cdot BU + c \cdot CT + d \quad (2)$$

The value α, IE, BU and CT could be defined as array with 1000 conditions as Equation 3 and organize as Equation 4.

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_{999} \\ \alpha_{1000} \end{bmatrix} = a \cdot \begin{bmatrix} IE_1 \\ IE_2 \\ \vdots \\ IE_{999} \\ IE_{1000} \end{bmatrix} + b \cdot \begin{bmatrix} BU_1 \\ BU_2 \\ \vdots \\ BU_{999} \\ BU_{1000} \end{bmatrix} + c \cdot \begin{bmatrix} CT_1 \\ CT_2 \\ \vdots \\ CT_{999} \\ CT_{1000} \end{bmatrix} + d \quad (3)$$

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_{999} \\ \alpha_{1000} \end{bmatrix} = \begin{bmatrix} IE_1 & BU_1 & CT_1 & 1 \\ IE_2 & BU_2 & CT_2 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ IE_{999} & BU_{999} & CT_{999} & 1 \\ IE_{1000} & BU_{1000} & CT_{1000} & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \quad (4)$$

Therefore, it is possible to applicate least square fitting for value α. The calculation has been performed with python code as other modules in this paper. Then, the value of **a**, **b** and **c** have been calculated and rewrite Equation 2 as Equation 5.

$$\alpha = -1.1481 \times 10^{-3}(IE) + 1.4025 \times 10^{-4}(BU) + 4.2671 \times 10^{-5}(CT) + 1.3824 \times 10^{-2} \quad (5)$$

## 4. Results

ANN, which is a sort of machine learning, is composed of at least 3 layers which are input, hidden, and output layers. The first layer is composed of input neurons. These neurons send data to deeper layers until it reaches to output layer. ANN train the data with the hidden layers between input and output layers, and it has the process to minimize the error between trained data and original data. In this study, ANN learn the patterns between initial conditions and value α to predict the data which is not calculated by the codes. The ANN has been developed with python code as other modules in this paper.

The initial conditions in Table 1 and the results from MCNP, which converted as value α, have been trained for ANN. The quarter of original dataset have been chosen for test data, and rest of dataset have been chosen for training dataset for ANN. The ANN shown as Figure 6 has been applied for predicting the value α.

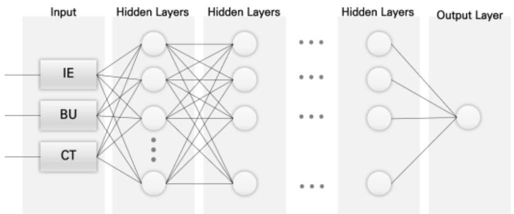


Figure 6. The schematic view of applied ANN

The value α in 1000 output have been arranged, and all output values are plotted in Figure 7.

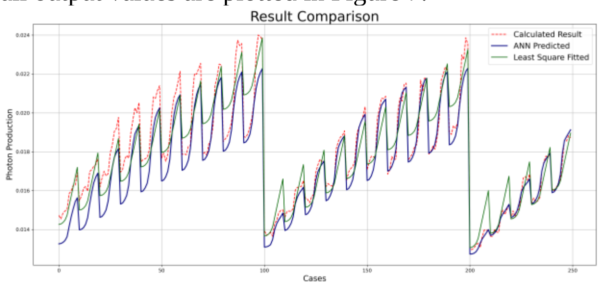


Figure 7. Results comparison between original dataset, ANN, and least square fitted data

The results have been compared with 250 cases from dataset. The case number has increased with the conditions as Table 2.

Table 2. Cases with initial conditions

| Cases | IE (wt%) | BU (GWd/MTU) | CT (years) |
|---|---|---|---|
| Case1 | 1.5 | 15 | 0.5 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case10 | 1.5 | 15 | 60.0 |
| Case11 | 1.5 | 20 | 0.5 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case20 | 1.5 | 20 | 60.0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case100 | 1.5 | 60 | 0.5 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case110 | 1.5 | 60 | 60.0 |
| Case111 | 2.0 | 15 | 0.5 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case120 | 2.0 | 60 | 60.0 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| Case1000 | 5.0 | 60 | 60.0 |

The shape of original data has shown increase with CT and BU, and the range of increase has shown larger with high burnup and long cooling time as shown with Case100 in Figure 7. However, in Equation 1, as α increase, the slope of original signal would show much steep than other cases.

With these characteristics, the ANN has learned the calculated results with initial conditions as given in Table 1 and 2. In Figure 7, the ANN predicted data has followed up original data as case number increases. Between case1 and case100, the predicted value could not cover all over the calculated results, however, the predicted values have followed up most part of the original data in the cases between 101 to 200. The predicted value has covered almost data of the original data over case201 in Figure 7. The results of ANN predicted values have shown that it requires much more learning data to predicted in accurate.

On the other hand, the least square fitted data was calculated with linearly. Therefore, it has shown that the shape of data in Figure 7 is increasing linearly as calculated. For the precise prediction to compare with original data, least square fitting equations would be required to be revised with exponential equations.

## 5. Conclusion

In this study, using depletion code to calculate out the spent fuel assembly composition, and Monte Carlo code to calculate out the NDA method. For decreasing the calculation times and time of organize inputs with outputs, python modules have been developed to organizing the overall processes. The artificial neural network has been applicated to show the possibilities of predicting the initial conditions of spent fuel assembly. The results of ANN have shown that it requires much more original data to learn for much accurate prediction. In addition, for the least square fitted results, it has shown that fitting equation requires to be replaced with exponential equations.

For the future work, the initial conditions would be increased more than 2,000 cases for machine learning, and the least square fitting equation would be calculated again with exponential fitting equation for much precise prediction. Some results have shown same values in different initial condition. Thus, it is necessary to consider other values from signals for distinguishing the similar values in the results.

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