Severe Accidents Estimation with Artificial Intelligence Learning Using Off-site Radiation Measurements Information

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***Keywords:** severe accident estimation, accident response, AI learning, MURCC

1. Introduction

In the Fukushima accident, communication between the nuclear power plant and radiation disaster prevention systems was disrupted, resulting in the unavailability of information from key operating parameters and off-site detector doses. Consequently, it is impossible to respond to the accident.

Japan Atomic Energy Agency (JAEA) has been operating a radiation disaster prevention system called System for Prediction of Environmental Emergency Dose Information (SPEEDI). SPEEDI analyzes environmental impacts, such as atmospheric concentrations and radiation doses of radioactive materials, during emergencies. It utilizes source term information, weather conditions, and geographic information. In the Fukushima accident, the operator of SPEEDI was unable to calculate the dispersion of the radioactive plume due to a communication disconnect between SPEEDI and the power plant.

Similarly, the Korea Institute of Nuclear Safety (KINS) has been operating a radiation disaster prevention system called the Atomic Computerized Technical Advisory System for Radiological Emergencies (AtomCARE). AtomCare also cannot be used for accident response without key operating variables and offsite radiation dose information.

Severe accidents, as defined, involve "significant damage to the reactor core" or “core meltdown” with potential for large release of radioactive products to the environment. In severe accidents, key operating parameters significantly impact decision-making during emergency response. When key operating parameters are unavailable, it is necessary to estimate internal plant information using off-site radiation data.

Table 1 categorizes whether the plant's key operating parameter and off-site radiation measurement data are transmitted to the radiation disaster prevention system in the event of a severe accident. It also classifies the possibilities of accident response based on the transmission status.

Table 1. Accident response based on connection between power plants and off-site emergency management center

Cases	Nuclear power plant’s key operating parameter	Off-site radiation monitoring instrument	Accident response
Case 1	Connected	Connected	Possible
Case 2	Unconnected	Connected	Impossible
Case 3	Unconnected	Unconnected	Impossible

In Case 1, the communication lines between the nuclear power plant and the off-site emergency operations center. Key operating parameters of a nuclear power plant are accessible. In this case, key operating parameters are transmitted to the radiation disaster prevention system in order to facilitate the response to accidents. In Case 2, the connectivity between the nuclear power plant and the off-site emergency operations center is disrupted. In this case, it is impossible to respond to the accident because of the source term. In Case 3, the scenario is the Fukushima accident [2]. Communication with internal and external power plants has been disrupted. Key operating parameters and off-site radiation monitoring instruments are currently unavailable. In this case, the source term cannot be calculated, and it is impossible to respond to the accident.

From Table 1, it is impossible to respond to Cases 2 and 3 because the plant's key operating parameters are not transmitted to the off-site emergency management center. However, in Case 2, off-site radiation information is available. We can respond to the accident by making an estimation of the plant's condition based on off-site radiation data.

Fig. 1. shows an accident at a single nuclear power plant, referred to as Case 2. Due to a severe accident, the connection between the power plant and the radiation disaster prevention system was severed. However, radiation monitoring instruments [3] located outside the plant can transmit information about radiation measurements to the radiation disaster prevention system. In this case, the off-site radiation dose information can be used to predict the conditions inside the nuclear power plant and inform accident response.

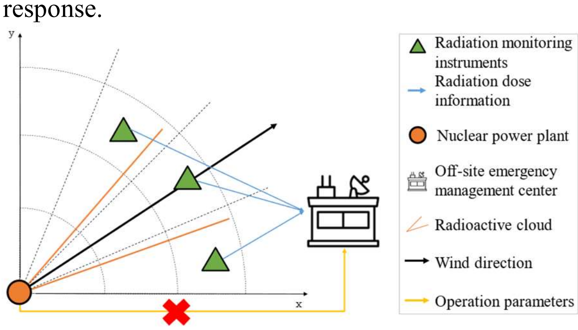

Fig. 1. Accident in a single unit

In this paper, for the first time, artificial intelligence is used to estimate the type of accident and the status of core damage in a nuclear power plant. This estimation is based on the analysis of off-site radiation monitoring instrument data. The main objective of this study is to develop a response strategy for a Case 2 accident.

2. Steps to train AI for accident estimation based on radiation information

Fig 2 shows the method for calculation in Case 2. The accident details of the nuclear power plant are obtained from the RASCAL code. The spread of radiation dose is calculated in MACCS using the source term information provided by RASCAL. We calculate the dose information at the radiation monitoring instrument locations using MURCC. Further details on the calculation steps are discussed in the subsections.

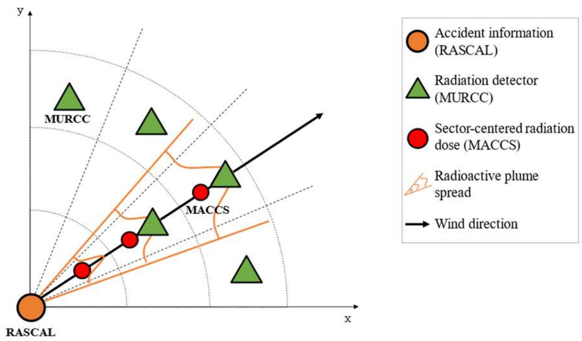

Fig. 2. Code used to calculate the accidents matched in Fig 1.

The training procedure for AI in the Case 2 accident is outlined in five steps, as depicted in Fig. 3. In the figure, N represents the type, size, and pathway of the radioactive leakage accident. D(x, y, t) denotes the two-dimensional nuclide concentration at a specific location at 15-minute intervals, calculated by MURCC. The AI training involves learning the functional expression N = f(D(x, y, t)), where f() represents the learned function. The trained AI model can then predict N when provided with D(x, y, t) information that was not used in training.

2.1 Selection of a nuclear power plant accident scenario and calculation of the source term

(Step 1) RASCAL [4] was a deterministic accident consequence assessment code provided by the U.S. Nuclear Regulatory Commission (NRC). RASCAL calculated the release of radioactive materials to the environment based on selected plant characteristics, accident type, accident size(N), release pathways, and release rates. RASCAL provides calculations for the total release of radioactive material, releases in 15-minute intervals, short-range plume model diffusion results, long-range puff model diffusion results, and doses to various human organs.
The total release of radioactive materials obtained from RASCAL calculations is used as input for MACCS (Step 2). Additionally, releasing radioactive materials at 15-minute intervals serves as input for MURCC(Step 3). The accident type and size selected for calculation are used as training data for AI training (Steps 4 and 5).

2.2 Calculation of off-site source concentration and radiation dose

(Step 2) MACCS [5] was a level 3 probabilistic accident consequence assessment code developed by Sandia National Laboratories (SNLs). MACCS input is based on the total release amount obtained from RASCAL. Additionally, MACCS input uses environmental information around the nuclear power plant and weather information (W) to calculate atmospheric diffusion and the off-site radiation effects. The time-cumulative radioactive substance concentration and atmospheric diffusion coefficient of the MACCS code are used as input for MURCC.

2.3 Post-processing to calculate source concentration and radiation dose at all points

(Step 3) The MURCC (Multi-unit Radioactive Consequence Calculation) [6] code was developed by the Integrated Nuclear Safety and Security Laboratory at Sejong University. MURCC calculated nuclide concentrations and doses at specific points on the ground surface. It uses one-dimensional Gaussian radiation cloud results from the MACCS code. MURCC can calculate nuclide concentrations and doses at receptor (radiation monitoring instruments) locations, considering emissions during specific time intervals.[6] In this step, MURCC's input is the time-cumulative radioactive substance concentration at the centerline of the radioactive cloud and the 15-minute interval radioactive material concentration from RASCAL.
In this study, calculation focused on Cs-137 as a nuclide. MURCC calculates the 15-minute interval radioactive concentration and dose f(D(x, y, t)) at each location. The nuclide concentration at specified instrument locations serves as training data for AI training.

2.4 AI training

(Step 4) The preprocessing of information obtained from MURCC included 12-hour doses at 15-minute intervals from five instruments, weather information for 12 hours during the accident, accident type, and accident size. The dose values were normalized to facilitate learning, and the accident type and size were preprocessed using one-hot encoding. The nuclide concentration D(x, y, t) at 15-minute intervals at the coordinates corresponding to the detector locations and the accident size and type (N) are used as training data for supervised learning. In this paper, the algorithms used for learning include Linear Regression [7], Decision Tree [8], Random Forest [9], XGBoost [10], and Deep Neural Network (DNN) [11].

After training, the accident's size and type can be estimated by the nuclide concentration on the detector locations at 15-minute intervals.

2.5 Testing trained AI

(Step 5) We employed two testing methods. The first method uses a data ratio of 7:3 for training and testing. The Second method uses all 900 data points and a test set of 90 randomly selected data points. The results from both methods were similar. Therefore, we decided to evaluate the results using the data ratio of 7:3.

3. Evaluation of AI learning results

The evaluation of AI learning results was based on accuracy and F1 score[12]. Accuracy measures the proportion of correctly predicted samples, while the F1 score is the harmonic mean of precision and recall. Precision measures the proportion of correctly predicted positive samples, and recall measures the proportion of actual positive samples that were correctly predicted.

3.1 Accuracy and F1 score.

Accuracy is a measure of how many of the total predictions made by the model are correct. It's the ratio of correct predictions to the total number of predictions. Mathematically, the accuracy can be calculated as Eq (1).

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

The F1 score is a metric that considers both precision and recall to provide a balanced measure of a model's performance. Precision is the ratio of true positive predictions to the total predicted positives, while recall is the ratio of true positive predictions to the total actual positives. Mathematically, precision and recall are defined as Eq (2).

$$Precicion = \frac{True\ Positives}{True\ Positives + False\ Positives}$$
$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

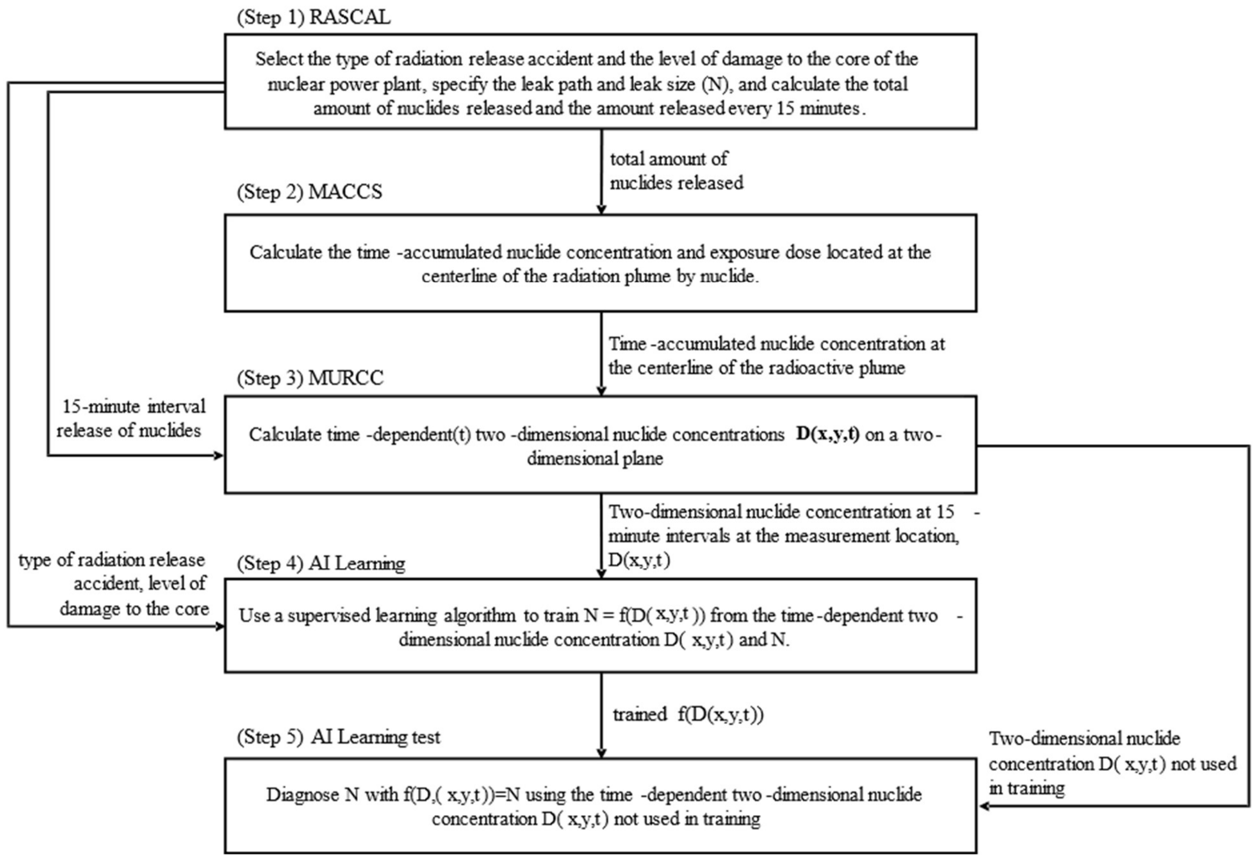

Fig.3. Steps to train AI for accident estimation based on radiation information

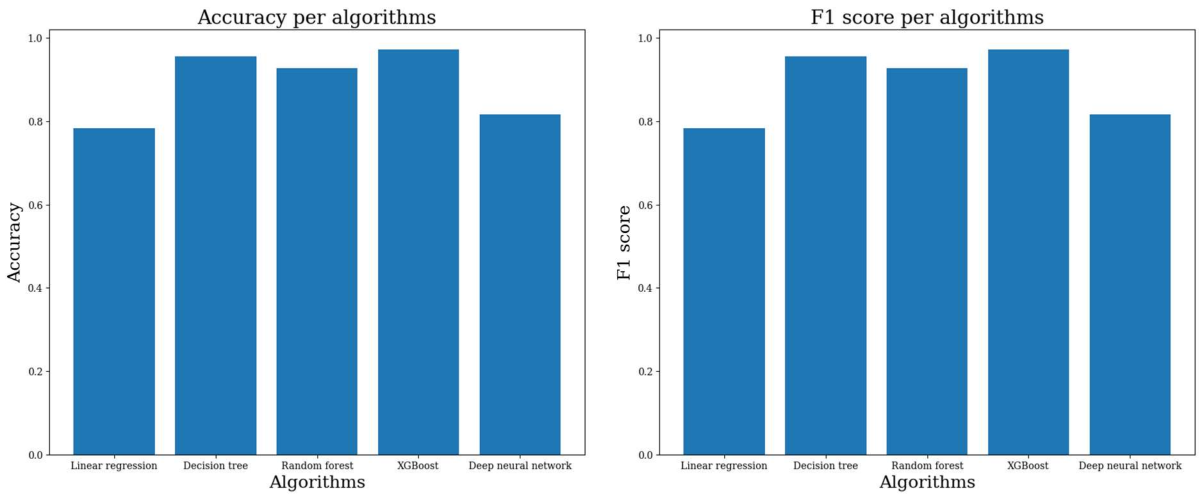

Fig. 4. Accuracy and F1 score of accident identification.

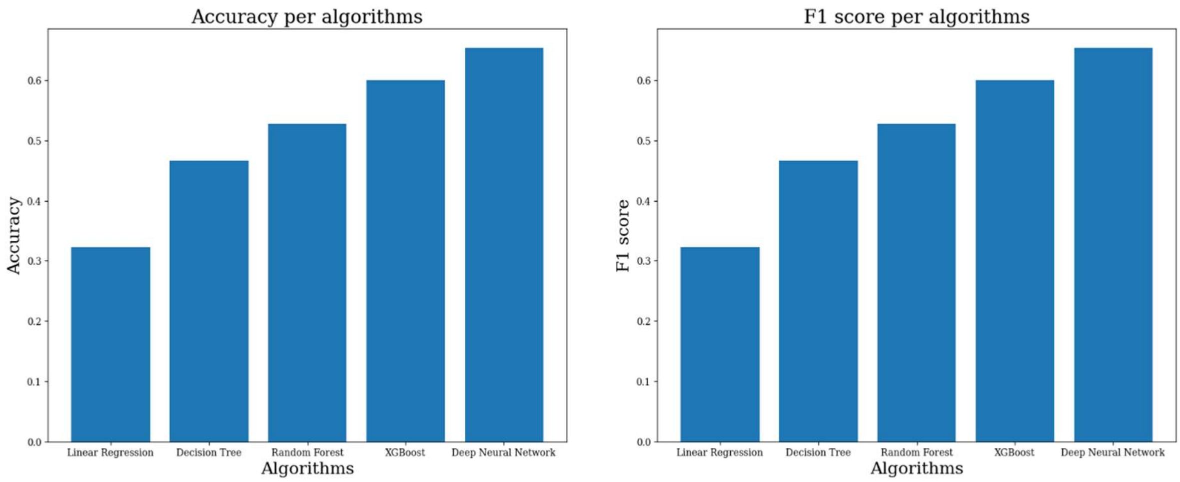

Fig. 5. Accuracy and F1 score of core damage status.

The F1 score is the harmonic mean of precision and recall, and it considers both false positives and false negatives. The formula for the F1 score is Eq (3).

$$F1 = 2 \times \frac{Precision + Recall}{Precision \times Recall} \quad (3)$$

3.2 Evaluating single accident AI learning results

In Fig. 4. The learning results for single unit accident classification showed that XGBoost achieved the highest accuracy and F1 score of 97% on the test data, while linear regression had the lowest accuracy but still classified with 78% accuracy and F1 score. The reason why Accuracy and F1 score have the same value is because all the incident data was provided uniformly.

Fig 5. is a classification of single-unit reactor core damage status. The DNN algorithm achieved the highest F1 score of 64% on the test data, while linear regression had the lowest F1 score of 32% on the test data.

4. Conclusions

This paper introduces the first study to use artificial intelligence technology to estimate accidents inside a power plant using off-site radiation information.

AtomCare is operated in Korea. If an accident similar to the Fukushima accident occurs, the AtomCare will not be available. To prepare for the case, using off-site radiation to classify severe accidents at nuclear power plants and predict their trends is necessary.

The results show that the relationship between core damage status and the Cs-137 nuclide dose is difficult to distinguish. In addition, the current AI training requires 12 hours of information to determine the accident classification and accident size. To compensate for this, the AI should be able to classify the accident classification and accident size with less time for dosimetry information. This paper only estimates single-unit accidents. It is necessary to conduct future research on multi-unit accident estimation.

Acknowledgements

This work was supported by the Korea Foundation Of Nuclear Safety (KOFONS) grant funded by the Nuclear Safety and Security Commission (NSSC), Republic of Korea (No. 2106062-0323-SB110 and 2204017-0223-SB110).

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